Occupancy Maps for Autonomous Driving and Robotics:
From Sensor Measurements to Environment Perception

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NXP Semiconductors, Eindhoven
Delft University of Technology*

Basics of ADAS

Advanced **D**river
Assistance **S**ystem



1.35 million road accidents deaths every year

A further **50 million** are injured



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Advanced driver assistance system (ADAS) improves driving comfort and road safety



SAFETY SYSTEM FIELD EFFECTIVENESS

HIGH-INTENSITY DISCHARGE (HID) HEADLIGHTS

▼ 21% NIGHTTIME ANIMAL/PEDESTRIAN/ BICYCLIST CRASHES

INTELLIBEAM

▼ 35% NIGHTTIME ANIMAL/PEDESTRIAN/ BICYCLIST CRASHES

FORWARD COLLISION ALERT

▼ 21% REAR-END STRIKING CRASHES

FORWARD AUTOMATIC BRAKING W/ FORWARD COLLISION ALERT

▼ 46% REAR-END STRIKING CRASHES

LANE KEEP ASSIST W/ LANE DEPARTURE WARNING

▼ 20% LANE DEPARTURE CRASHES

LANE CHANGE ALERT W/ SIDE BLIND ZONE ALERT

▼ 26% LANE CHANGE CRASHES

REAR VISION CAMERA

▼ 21% BACKING CRASHES

REAR PARK ASSIST

▼ 38% BACKING CRASHES

REAR CROSS TRAFFIC ALERT W/ REAR VISION CAMERA & REAR PARK ASSIST

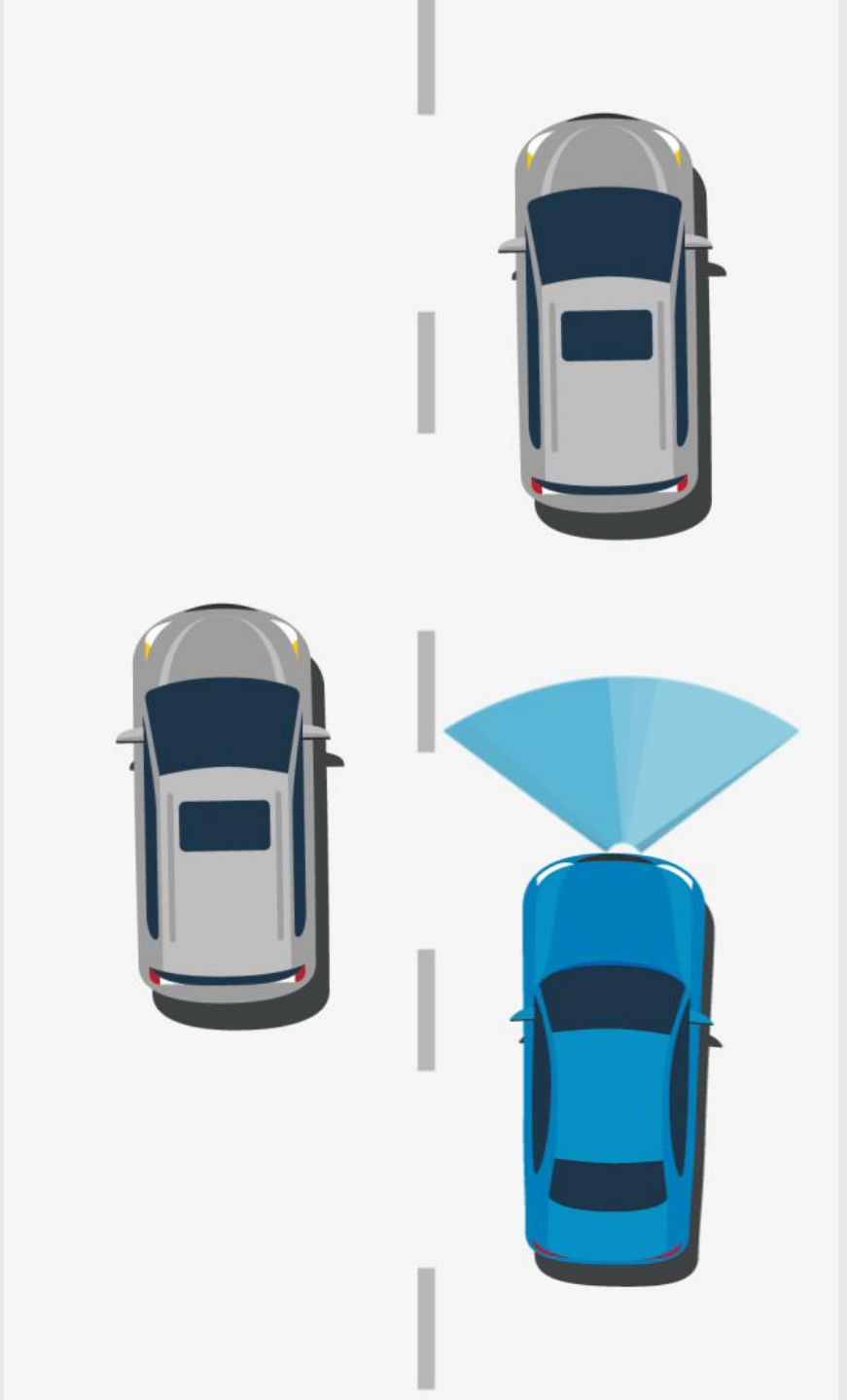
▼ 52% BACKING CRASHES

REVERSE AUTOMATIC BRAKING W/ REAR CROSS TRAFFIC ALERT, REAR VISION CAMERA & REAR PARK ASSIST

▼ 81% BACKING CRASHES

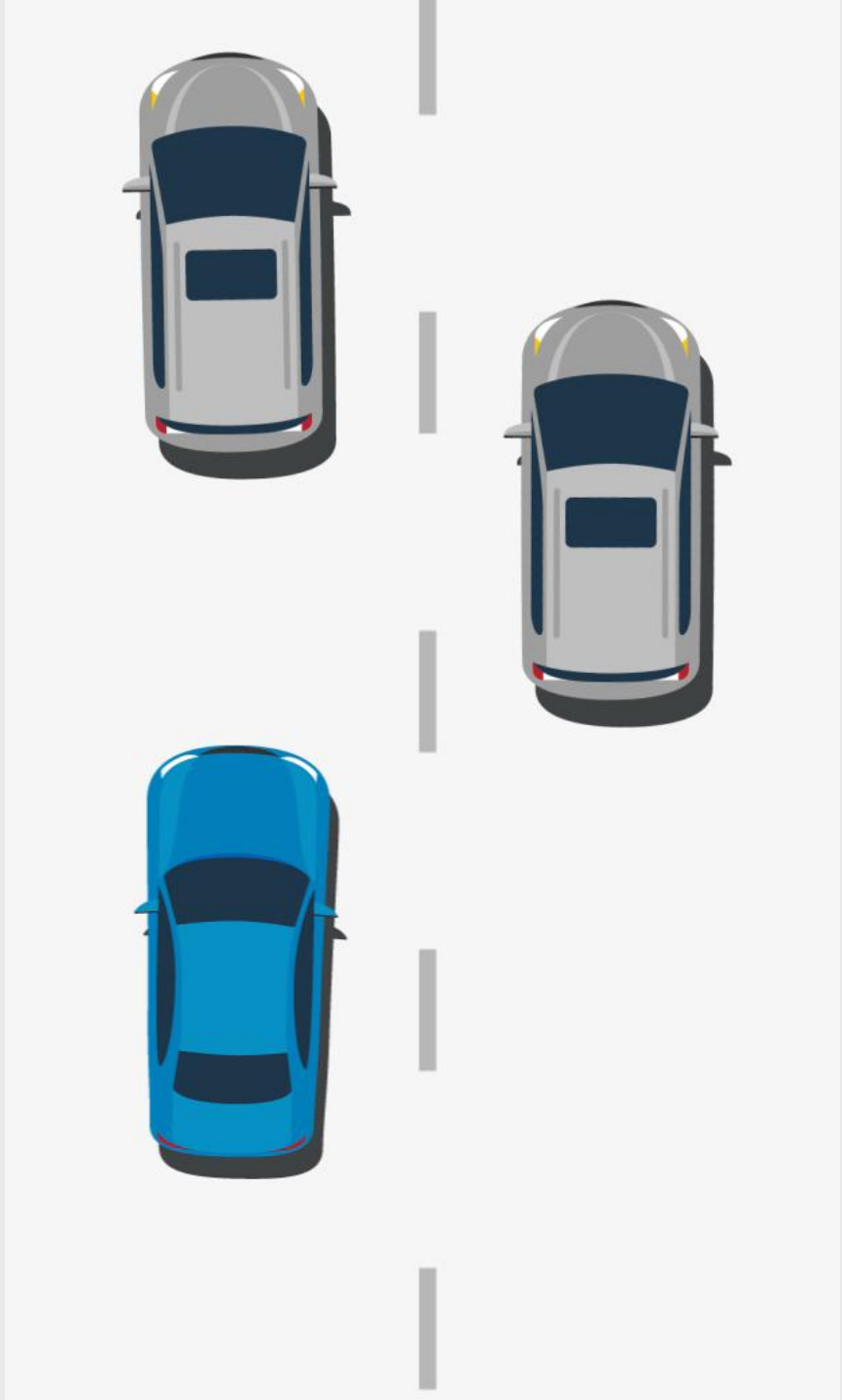
UMTRI REPORT 2019-6

ADAS: Adaptive cruise control



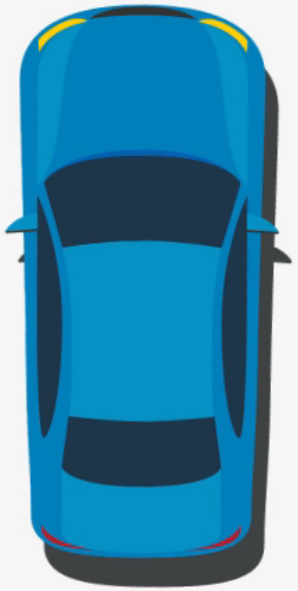
Source: NHTSA

ADAS: Lane departure warning



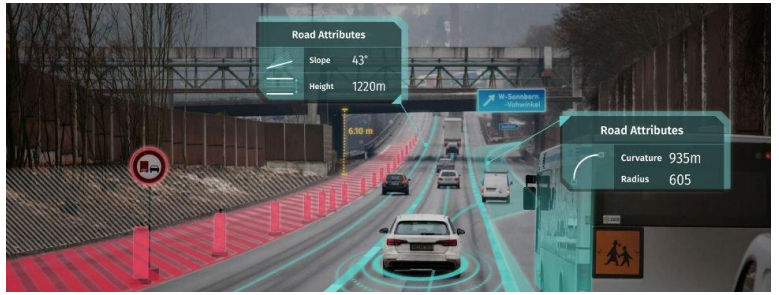
Source: NHTSA

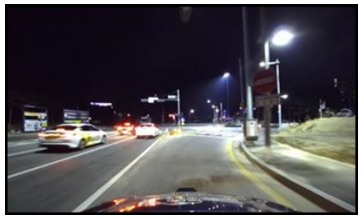
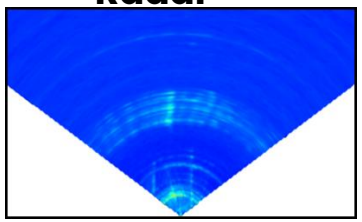
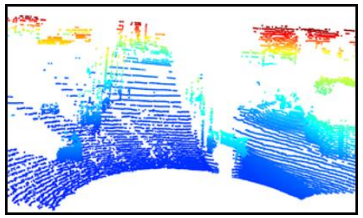
ADAS: Blind spot warning



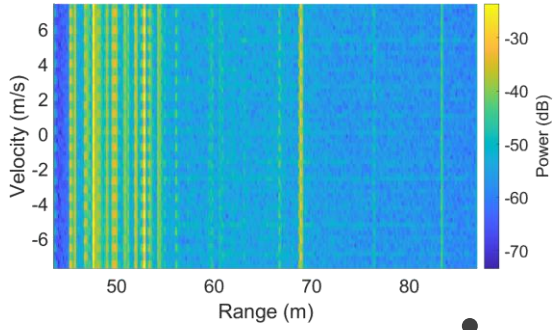
Source: NHTSA

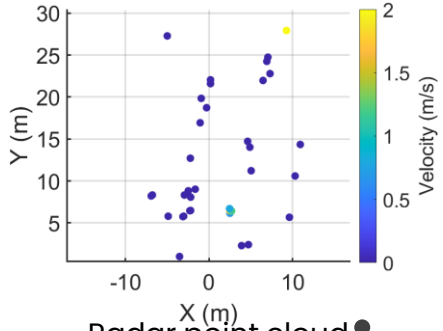
Sensors for ADAS



	Detection range	Distance	Resolution	Speed	Object classification	Scene semantics	Environment robustness
Vision 	++	–	++	+	++	+	–
Radar 	+++	+	+	++	+	–	+
LiDAR 	++	+	++	–	+	–	–

Radar processing chain: Radar measurements to point cloud





ADC samples

Receiver front-end

Range FFT

Doppler FFT

Detection filtering

Direction-of-arrival estimation

Radar point cloud

Perception chain

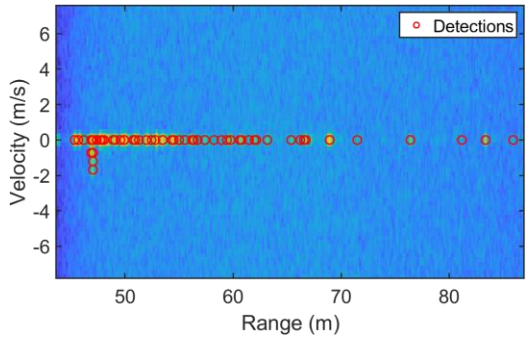
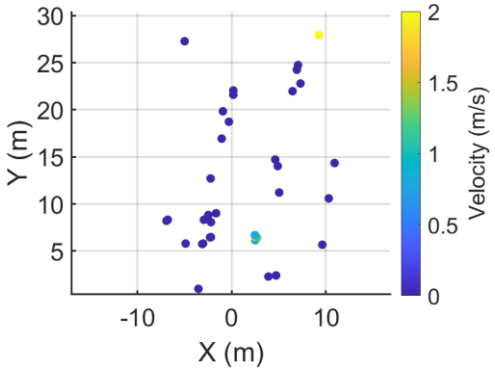
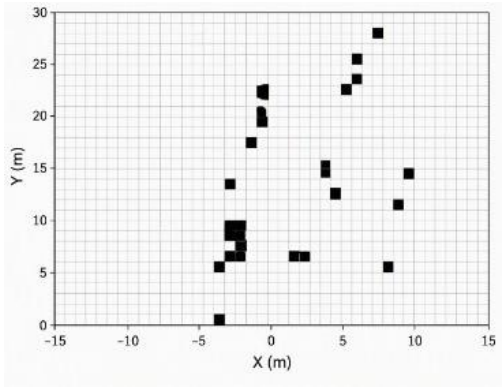


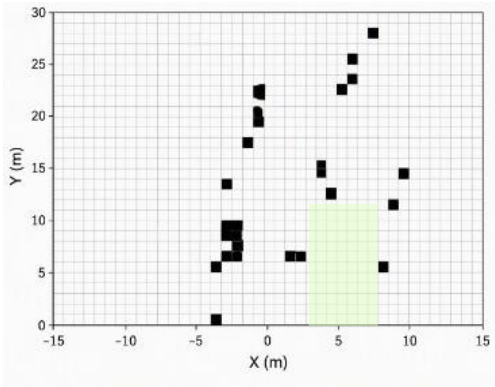
Image of scene

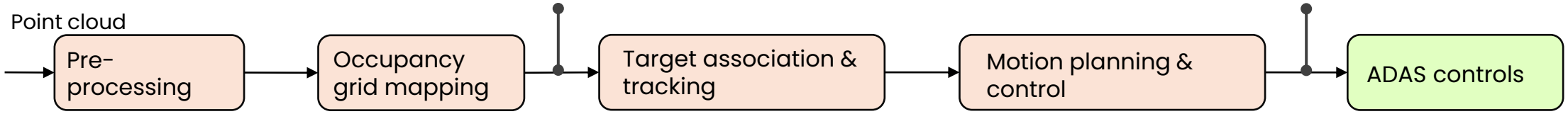


Radar perception chain: Occupancy Grid Mapping







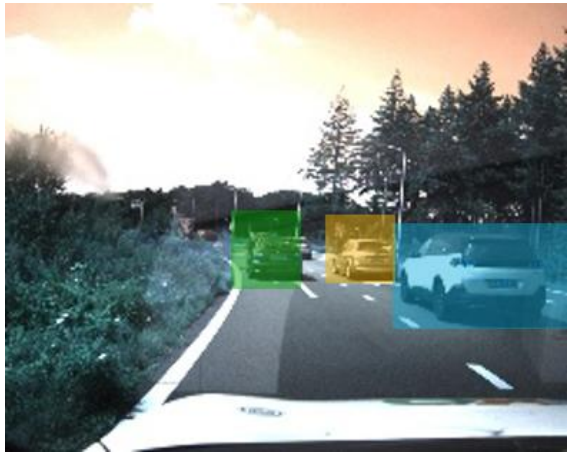


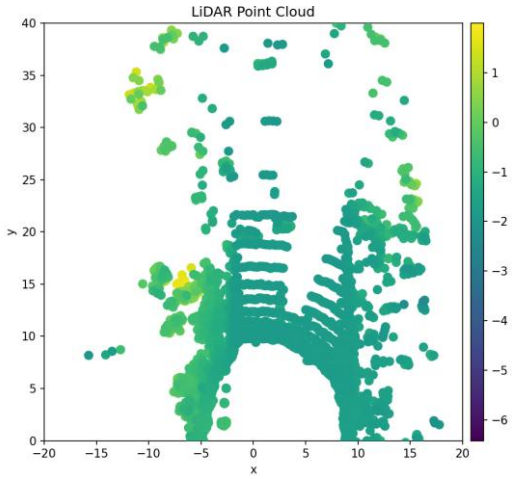
Occupancy grid mapping (OGM)

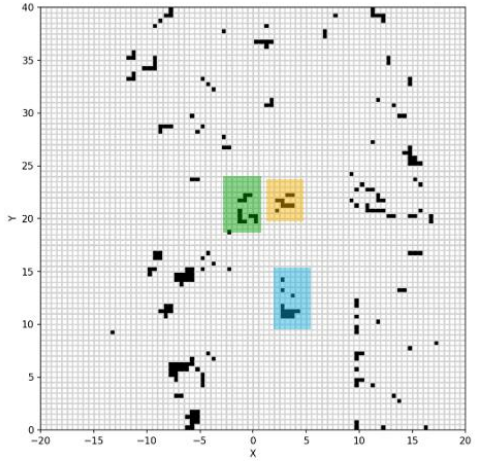
- Discrete representation of the environment as a grid of binary values
- Each cell is marked as either **occupied** or **free** based on point cloud measurements
- The grid typically has a uniform cell size that balances **precision** and **computational complexity**
- OGM supports downstream tasks such as **localization**, **obstacle avoidance,** and **planning**

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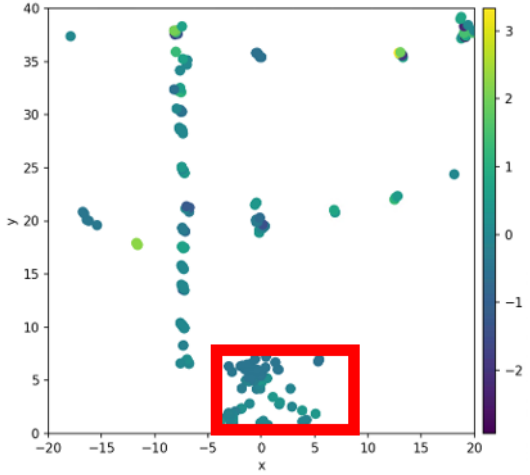
OGM with LiDAR and radar point cloud data

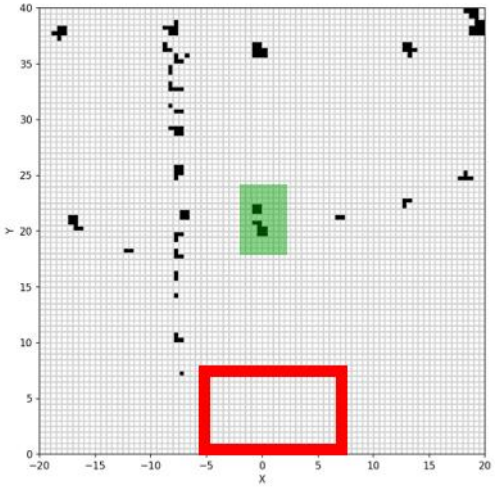












Mitigating **road reflections** and **multipath artifacts** in LiDAR and radar point cloud with OGM, while **determining obstacle boundaries**

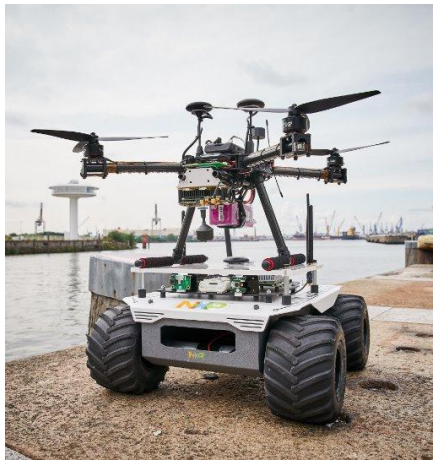
Safe Navigation in Robotics



AMRs in warehouses



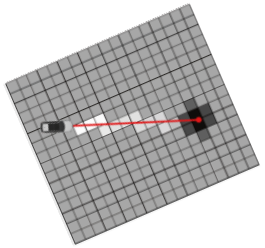
Outdoor delivery robots

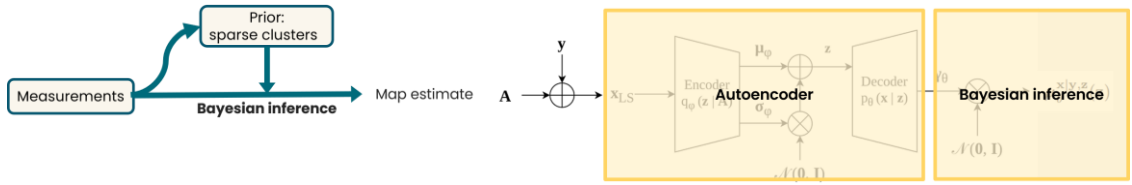


Drones

Outline

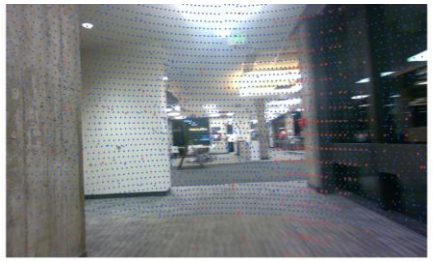
- OGM algorithms [**Geethu Joseph**]
  - Model-based
  - Learning-based
  - Physics-informed learning-based



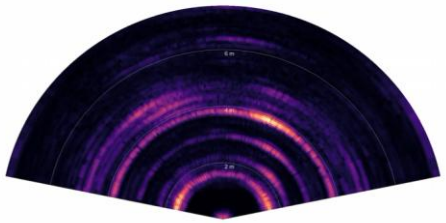


- Datasets and evaluation metrics [**Peiyuan Zhai**]

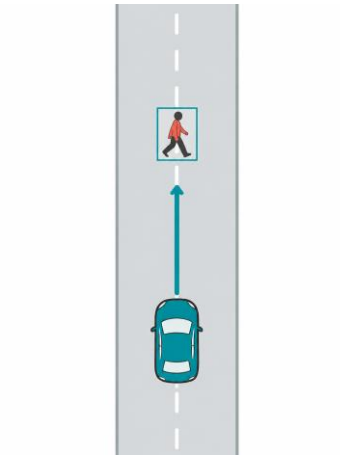




Camera



Radar intensity



Occupancy mapping algorithms



Occupancy Grid Mapping Problem



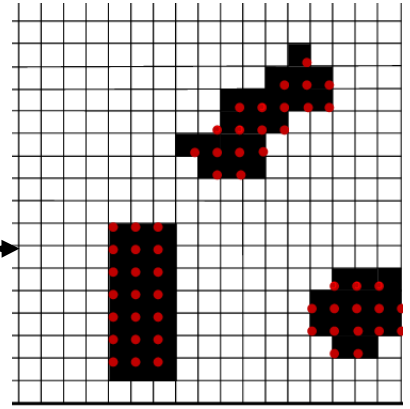
Grid size: task-dependent geometric detail.

Point cloud data

Grid creation

Mapping Algorithm

Estimate cells that are occupied by obstacles or free



Example from A. Sakai, "**Lidar to grid map,**" *PythonRobotics Documentation*, accessed Oct. 21, 2026.
D. Nuss et al., "**A random finite set approach for dynamic occupancy grid maps with real-time application**," Int. J. Robotics Research, 2018. doi: 10.1177/0278364918775523.

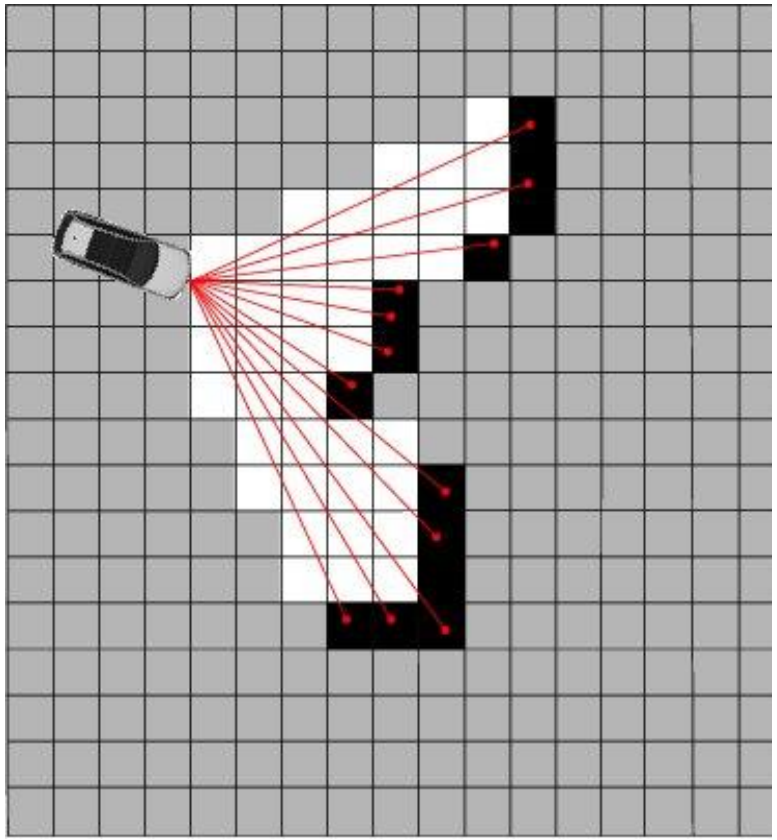
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Inverse sensor model: From measurements to probabilities

Sensor measurements need to be transferred to cell-wise occupancy probabilities.

Probabilistic maps accounts for uncertain and noisy sensor measurements

$P(o) = 0 \longrightarrow$ Free cells
$P(o) = 1 \longrightarrow$ Occupied cells
$P(o) = 0.5 \longrightarrow$ Unknown cells



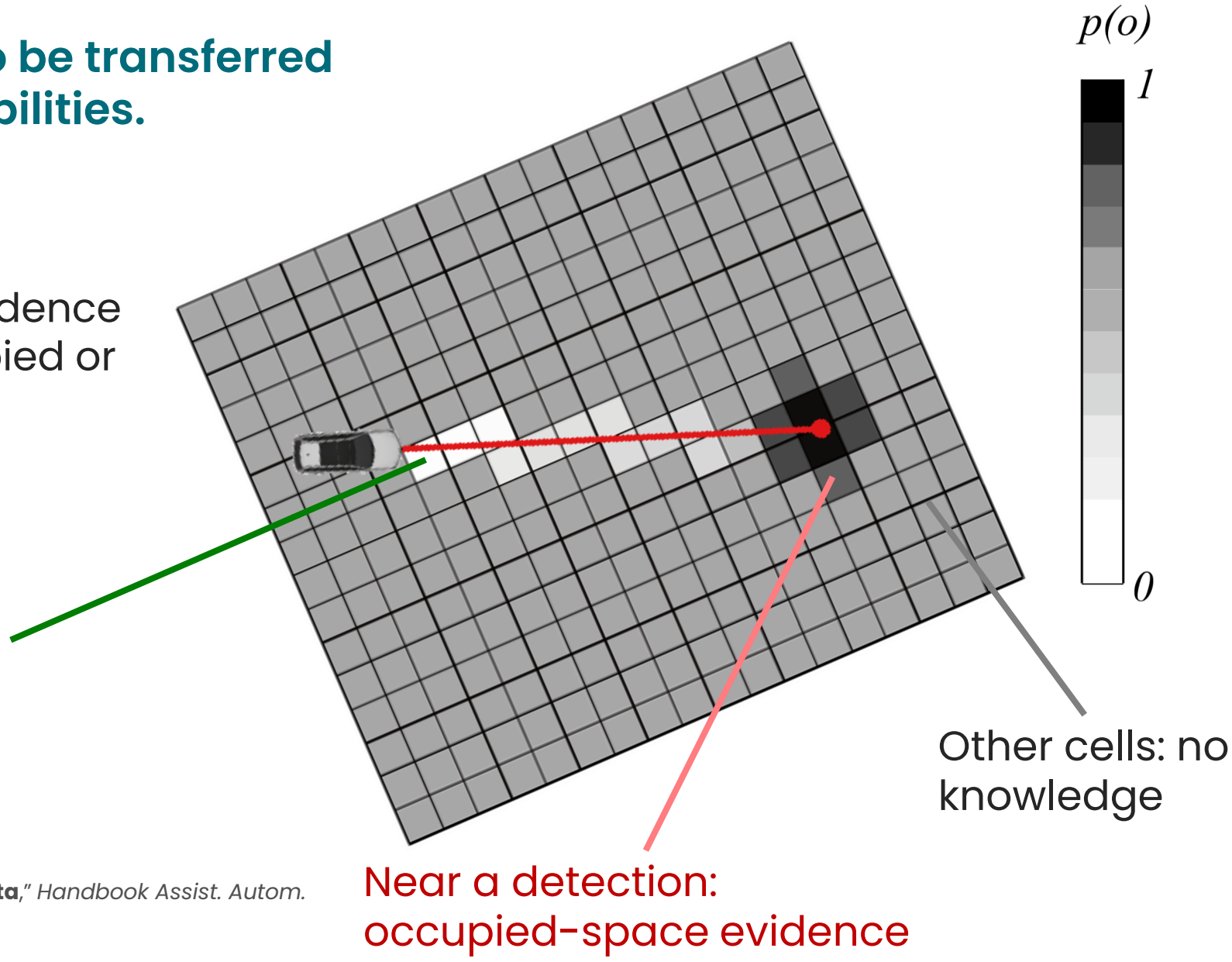
K. Dietmayer et al., "**Representation of Fused Environment Data**," *Handbook Assist. Autom. Driving*, 2026. doi: 10.1007/978-3-658-45276-6_20.

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Inverse sensor model

Sensor measurements need to be transferred to cell-wise occupancy probabilities.

Each measurement provides evidence about which grid cells are occupied or free, $p(o|z)$.

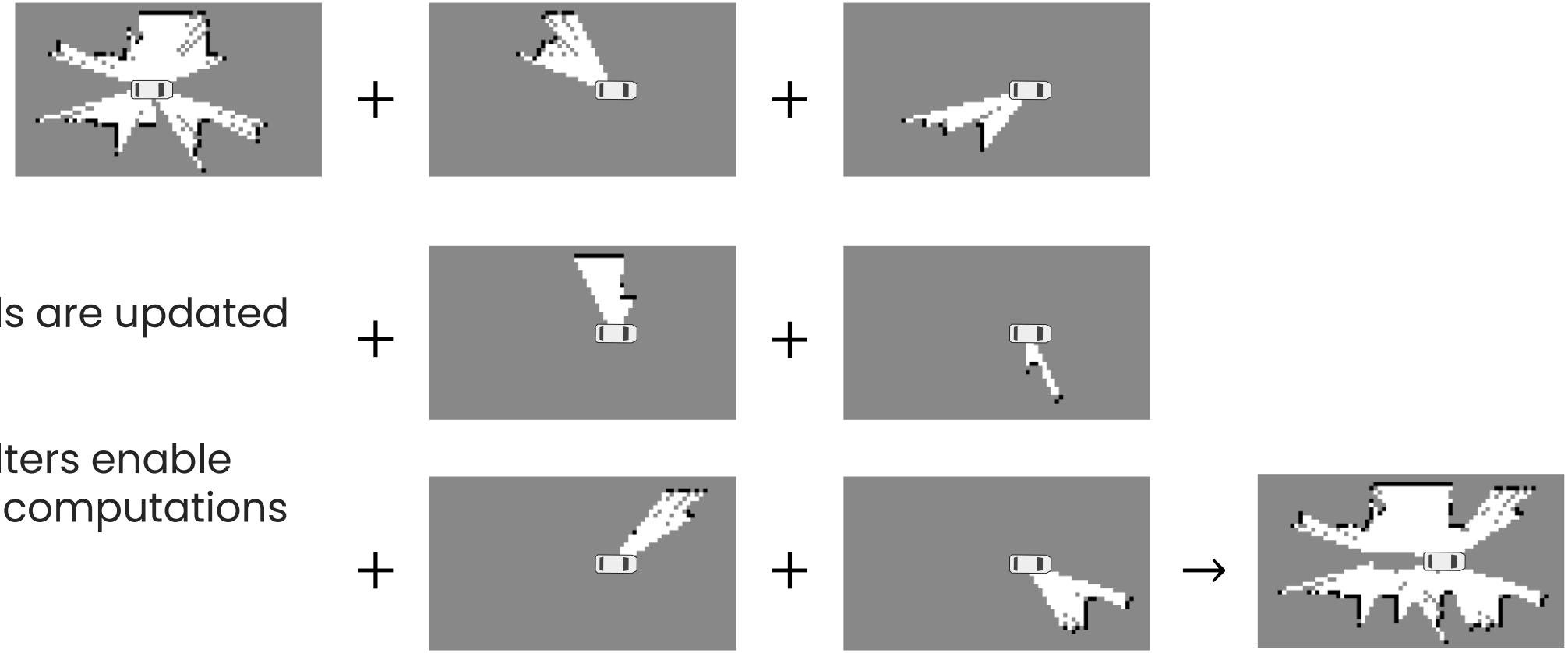


K. Dietmayer et al., "**Representation of Fused Environment Data**," *Handbook Assist. Autom. Driving*, 2026. doi: 10.1007/978-3-658-45276-6_20.

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Inverse sensor model-based OGM

Bayesian accumulation of evidence: Each new measurement updates the map



Assumption: Cells are updated independently

Feature: Binary filters enable fast and efficient computations

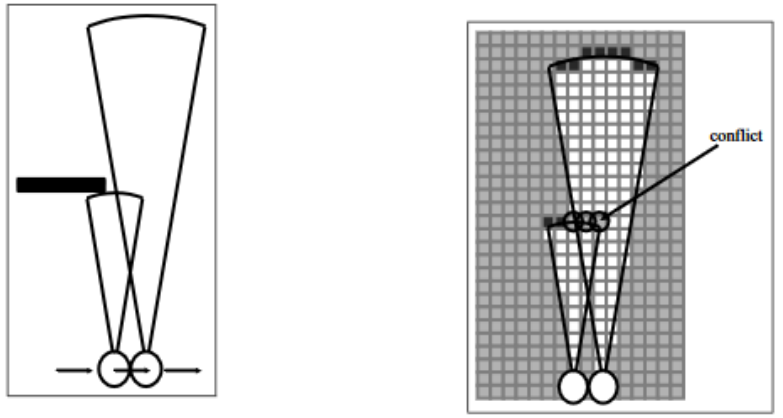
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Inverse sensor model-based OGM: Limitation

Independent cell-wise estimation struggles to resolve conflicting evidence and spatial ambiguity

Conflicting evidence: Inconsistent observations can lead to ambiguous maps

Spatial ambiguity: Local estimates may fail to capture global spatial context



Example: Two conflicting evidence about the same cell

S. Thrun, "**Learning Occupancy Grid Maps with Forward Sensor Models**," Auton. Robots, 2003. doi: 10.1023/A:1025584807625.

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Spatial correlation-aware Kernel-based OGM

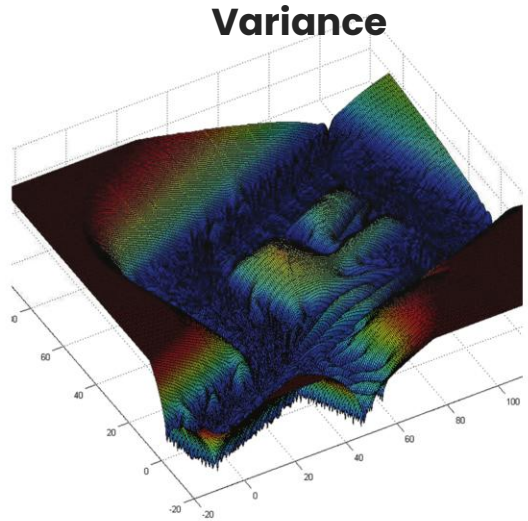
Model spatial data using a continuous Gaussian Process

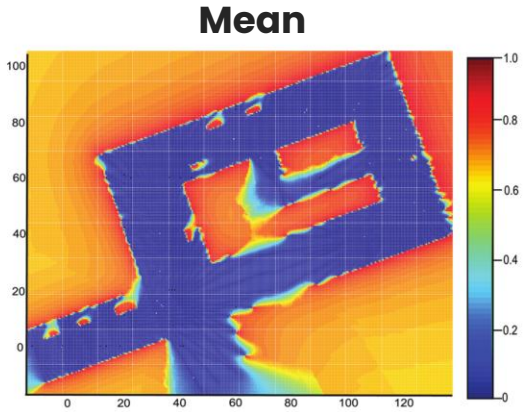
Spatial correlation: Shares information across locations

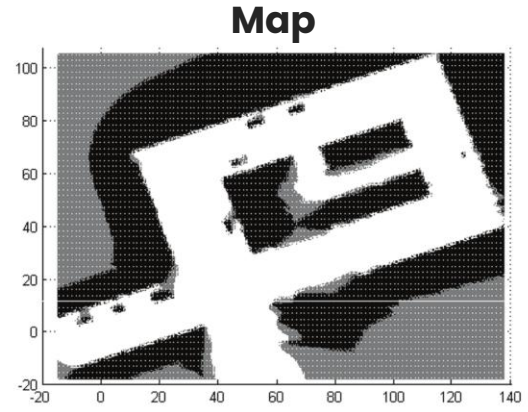
Smooth predictions: Captures spatial patterns

Uncertainty estimation: Indicates where predictions are less reliable

Limitation: Computational cost can be high for large maps.





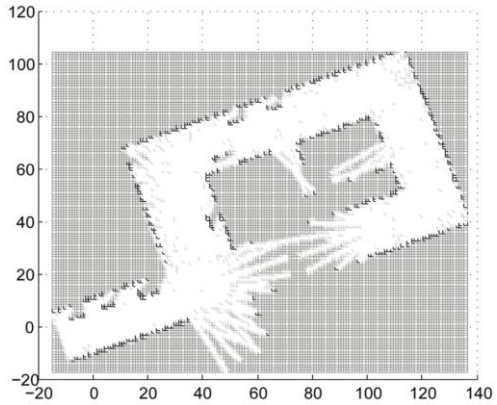


S. T. O'Callaghan & F. T. Ramos, "**Gaussian process occupancy maps**," IJRR, 2012. doi: 10.1177/0278364911421039.

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Classical occupancy mapping

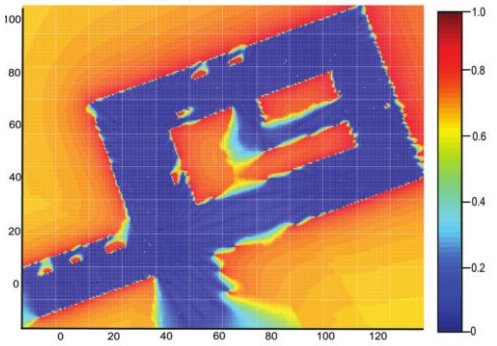
Explicit models connect measurements to occupancy and uncertainty.



Inverse sensor model

Fast and incremental computation.

Independence assumption may lead to mapping error.



Kernel-based methods

Spatial correlation considered by kernel structure.

Higher computation cost.

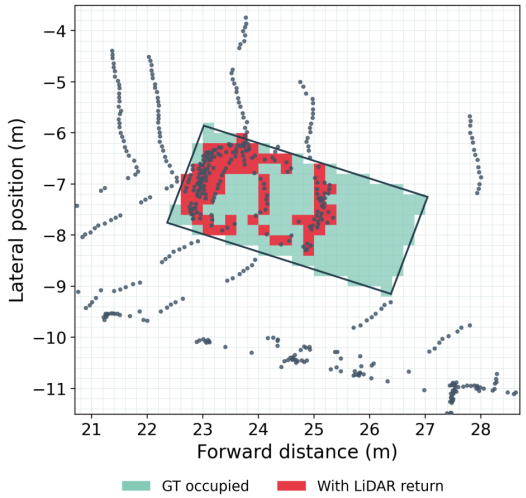
Next: Beyond correlation: smarter, faster, more robust mapping!

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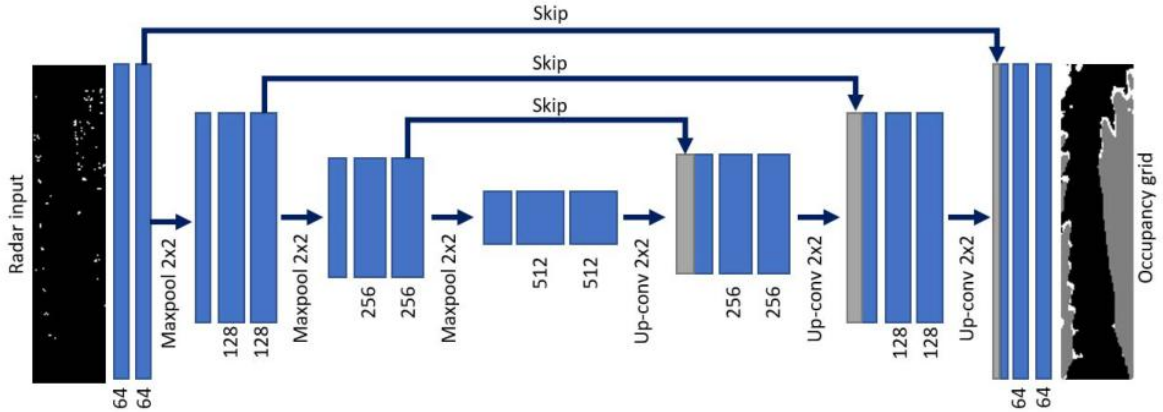
Learning-based occupancy mapping

State-of-the-art approaches beyond Gaussian Processes

Sparse Bayesian learning



End-to-end learning

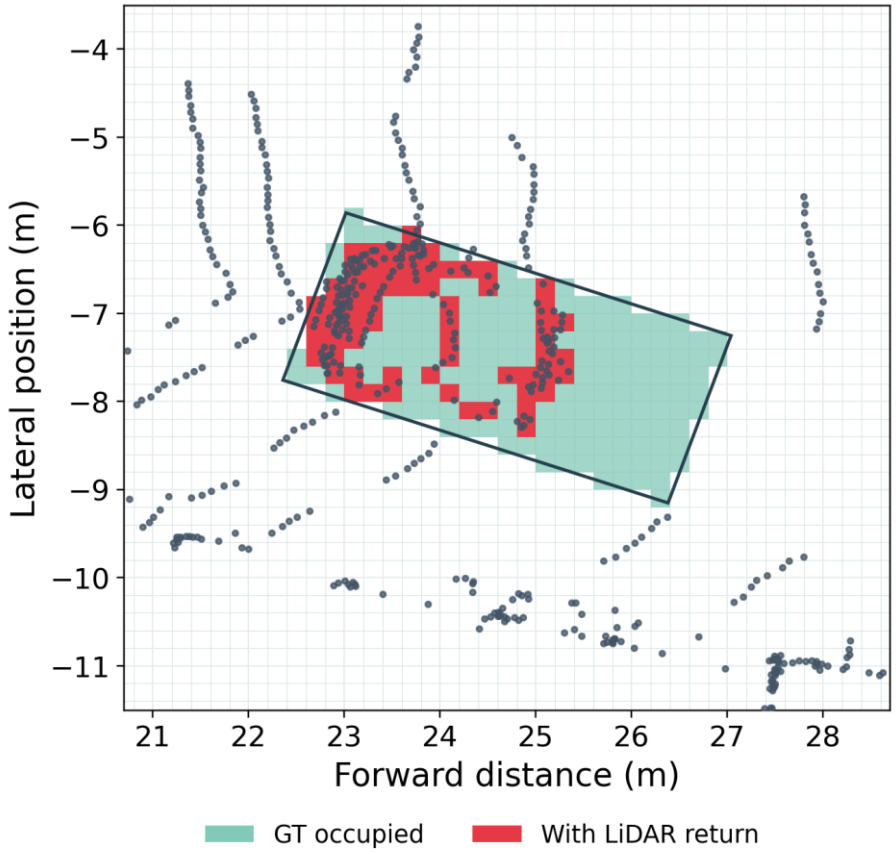


Capture complex environmental structures and improve mapping performance.

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Sparsity and spatial structure

Occupied cells can form small clusters



Real objects typically occupy groups of neighboring cells.

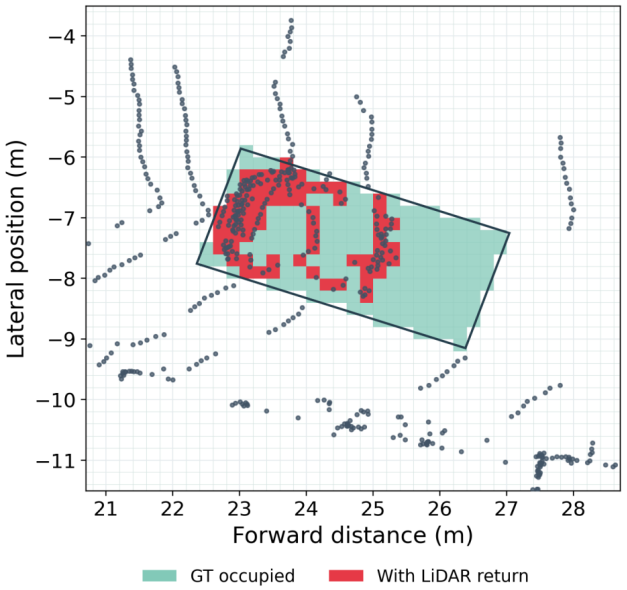
Sparse Bayesian learning: **construct prior distribution** that couples neighboring cells to promote block structure.

Ç. Önen et al., "Occupancy Grid Mapping for Automotive Driving Exploiting Clustered Sparsity," IEEE Sensors J., 2024.

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Sparse-Bayesian learning OGM

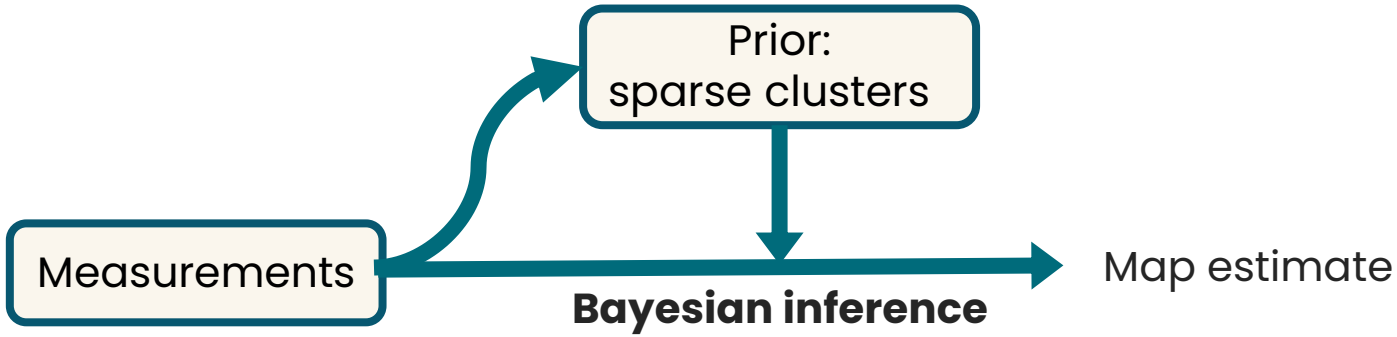
Model-based learning



Gaussian prior: Encodes assumptions about sparse, spatially clustered occupancy.

Linear measurement model: Relates sensor observations to the underlying occupancy map.

Bayesian inference: Combines the prior and measurements to estimate the occupancy map.



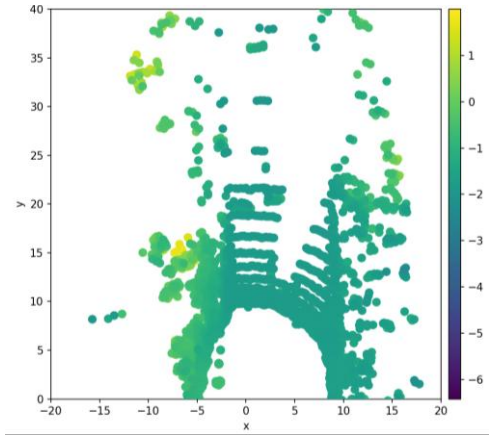
Ç. Önen et al., "Occupancy Grid Mapping for Automotive Driving Exploiting Clustered Sparsity," IEEE Sensors J., 2024.

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End-to-end data-driven learning

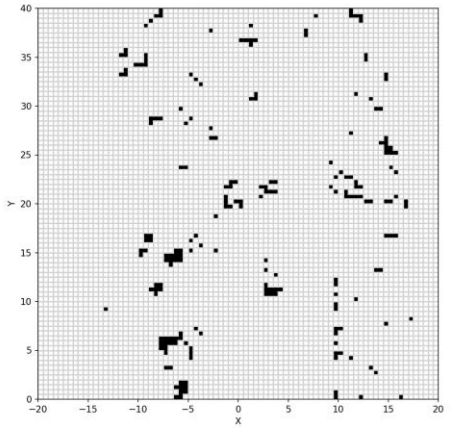
Learn the mapping directly using examples

Input



Learnable end-to-end network

Output



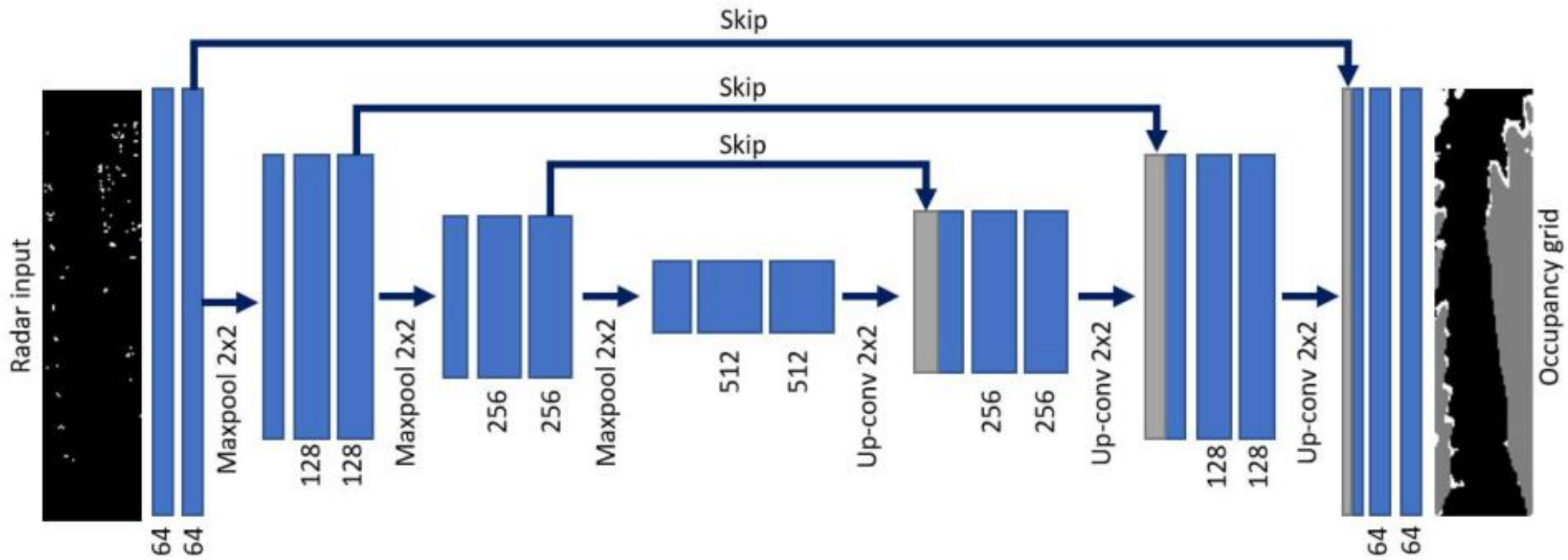
Blind / model-free approach: in the strict sense, no explicit physical model is required.

Fast inference after training and learns **complex patterns** from data.

L. Sless et al., "**Road Scene Understanding by Occupancy Grid Learning from Sparse Radar Clusters using Semantic Segmentation**," IEEE/CVF ICCVW, 2019. doi: 10.1109/ICCVW.2019.00115.

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Deep Learning an inverse sensor model with a CNN



L. Sless et al., "**Road Scene Understanding by Occupancy Grid Learning from Sparse Radar Clusters using Semantic Segmentation**," IEEE/CVF ICCVW, 2019. doi: 10.1109/ICCVW.2019.00115.

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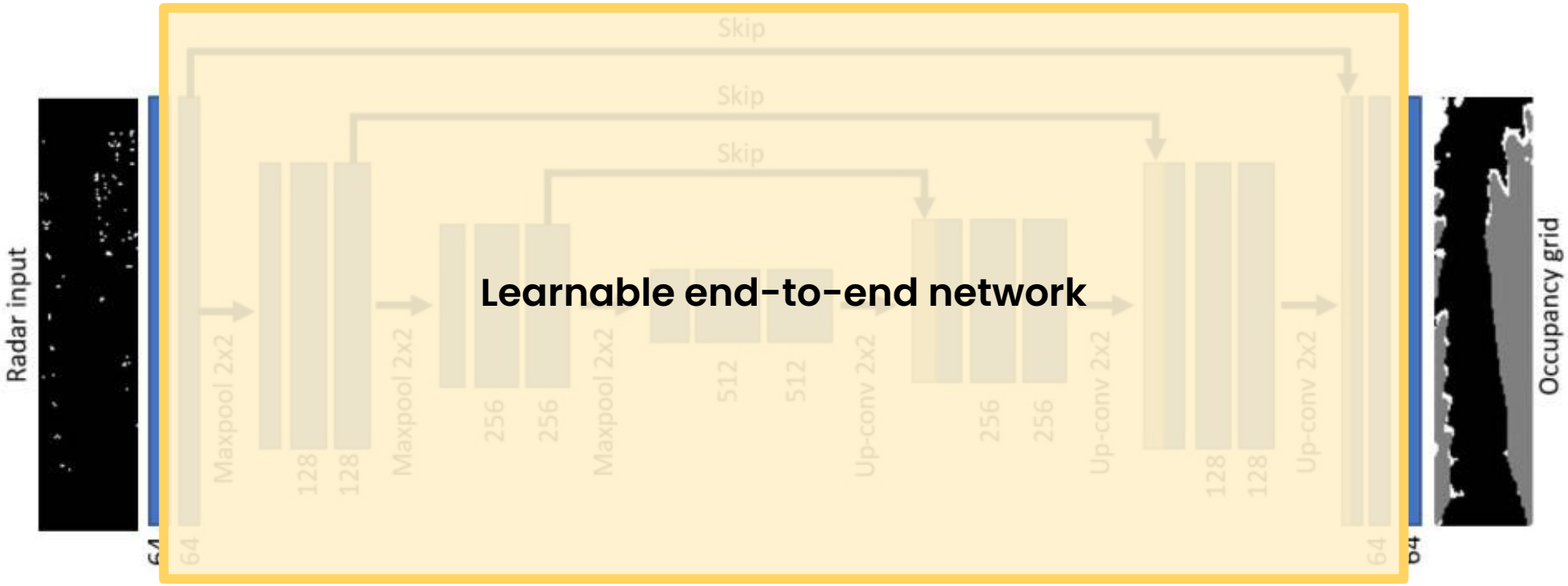
Deep Learning an inverse sensor model with a CNN

Input

Sparse radar detections
as a BEV image.

Output

Semantic output
as occupancy status



L. Sless et al., "**Road Scene Understanding by Occupancy Grid Learning from Sparse Radar Clusters using Semantic Segmentation**," IEEE/CVF ICCVW, 2019. doi: 10.1109/ICCVW.2019.00115.

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Model-based inference Vs data-driven learning

Sparse Bayesian learning	End-to-end learning
Physical consistent maps	Physical consistency not guaranteed
Explicit assumptions and interpretable	Less interpretable; uncertainty may be poorly calibrated
Lower dependence on labeled data	Requires large labeled datasets; Often poor generalization
Struggle with complex real-world patterns	Learns complex spatial features from data can be hard to explain.
Computationally expensive	Fast inference after training

Next: Can we get structure, learning, and speed—all in one?

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From Learning to Reliable Mapping

Bayesian learning

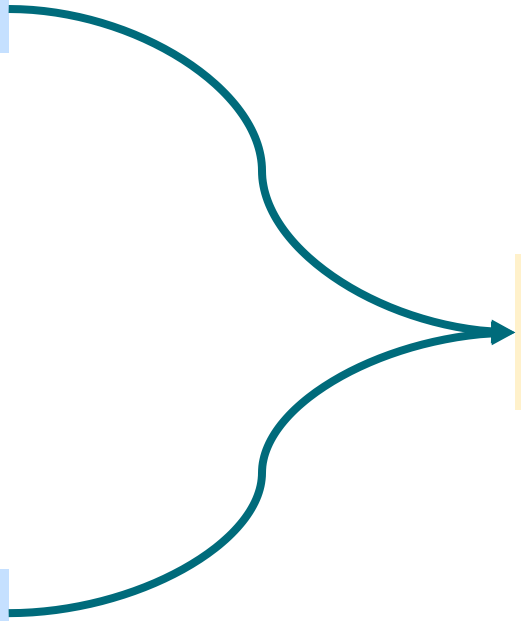
Hand-designed rules and parameters

Predictable, interpretable behavior

Learnable layers

Parameters optimized from data

Learn complicated real-world data from examples



Physics informed learnable methods

Learn only what needs to be learned.

Keep known geometry, physical constraints, and safety-critical logic explicit.

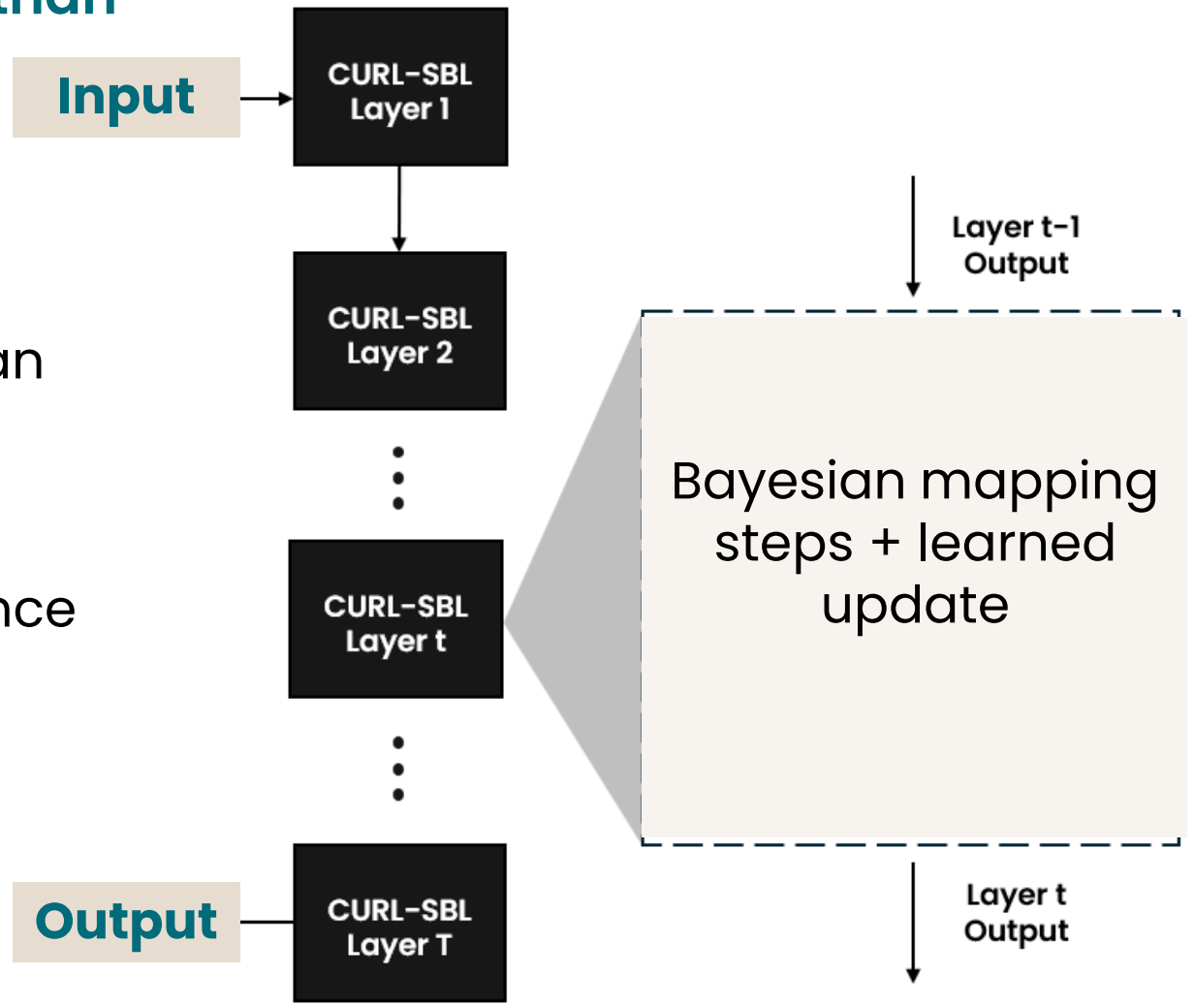
NXP Public

CURL-SBL: a learned update within Bayesian inference

Replace a hyperparameter update rather than directly modifying the map

Unrolling converts a fixed number of Bayesian learning iterations into network layers.

Each layer progressively refines the map estimate by combining model-based inference with neural network-based updates.



N. Fotopoulos et al., "**CNN Unrolled Sparse Bayesian Learning for Automotive Occupancy Grid Mapping**," IEEE Sensors J., 2026. doi: 10.1109/JSEN.2026.3703917.

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CURL-SBL: a learned update within Bayesian inference

Unrolled version of sparse Bayesian learning

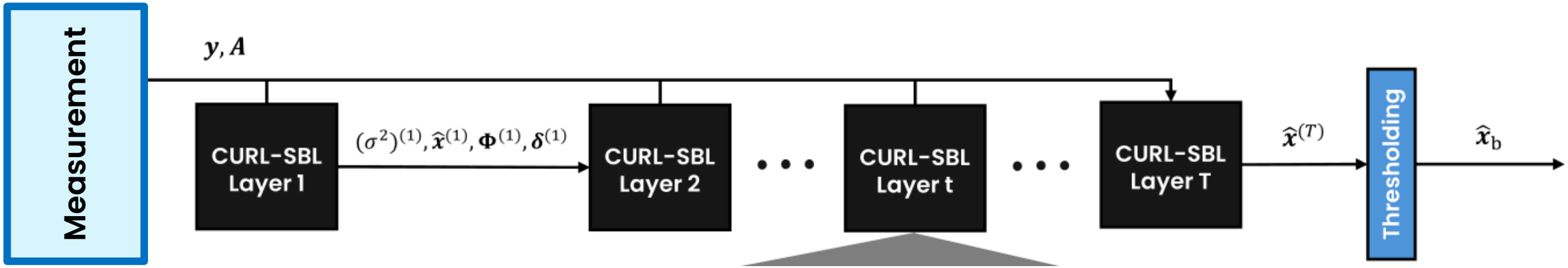


N. Fotopoulos et al., "**CNN Unrolled Sparse Bayesian Learning for Automotive Occupancy Grid Mapping**," IEEE Sensors J., 2026. doi: 10.1109/JSEN.2026.3703917.

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CURL-SBL: a learned update within Bayesian inference

Unrolled version of sparse Bayesian learning

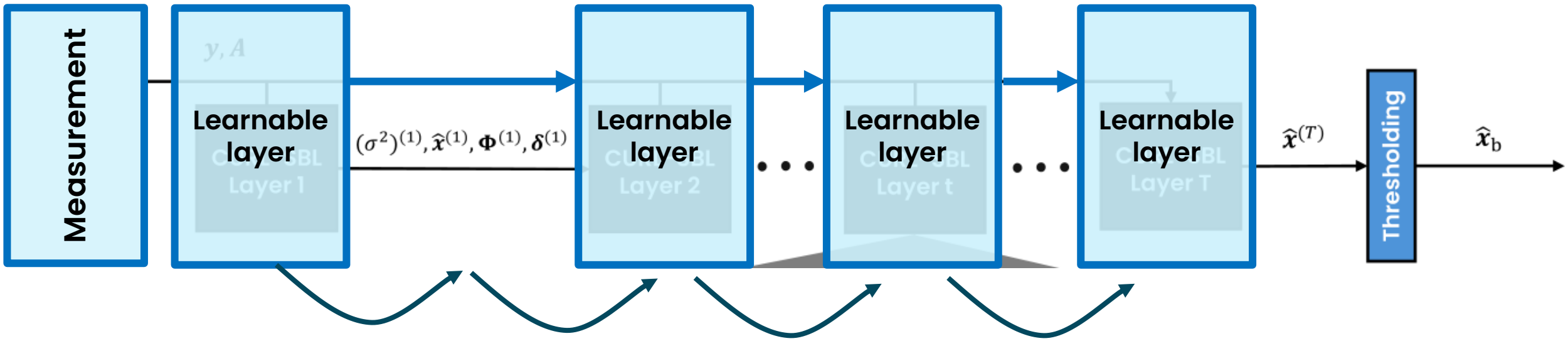


N. Fotopoulos et al., "**CNN Unrolled Sparse Bayesian Learning for Automotive Occupancy Grid Mapping**," IEEE Sensors J., 2026. doi: 10.1109/JSEN.2026.3703917.

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CURL-SBL: a learned update within Bayesian inference

Unrolled version of sparse Bayesian learning



Learned block

A small **CNN** updates the spatial sparsity pattern.

Explicit block

Compute the map, covariance and noise level.

N. Fotopoulos et al., "**CNN Unrolled Sparse Bayesian Learning for Automotive Occupancy Grid Mapping**," IEEE Sensors J., 2026. doi: 10.1109/JSEN.2026.3703917.

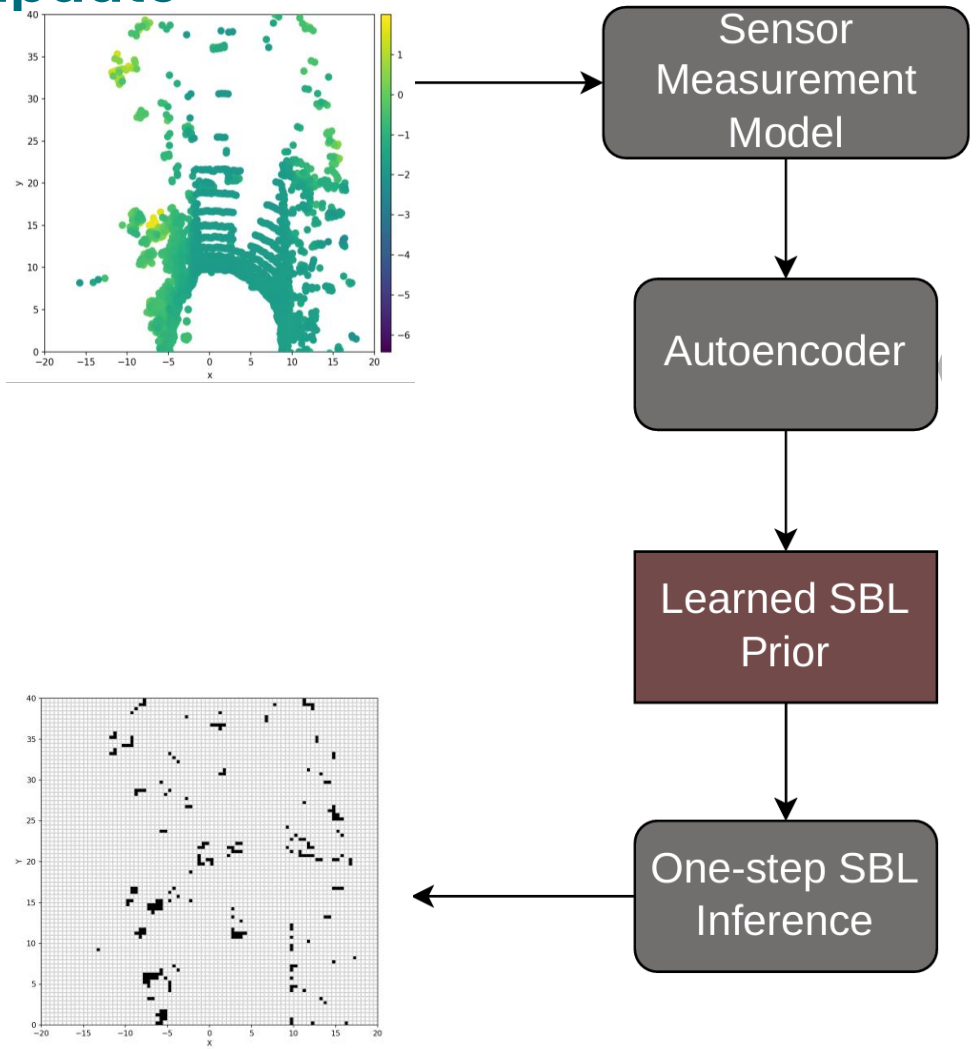
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AE-SBL: a sparse-aware Bayesian autoencoder

Autoencoder learns the prior instead of learning update

Autoencoder: Learns patterns in signals from training data to learn prior hyperparameters

Sparse Bayesian learning inference: Encourages sparse solutions, using sensor model and learned hyperparameters

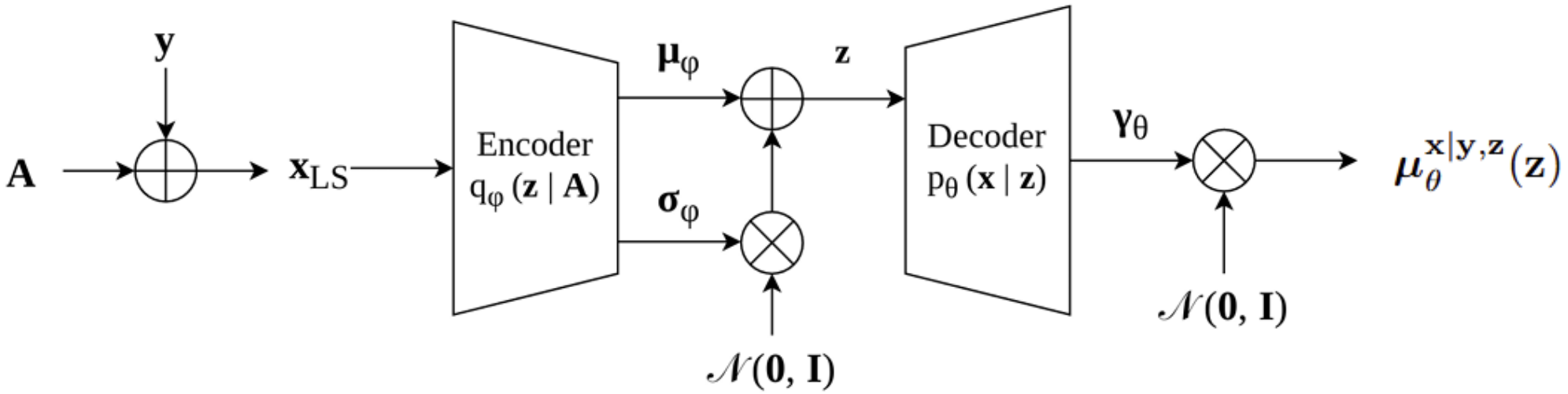


H. Jia et al., "**Sparse Bayesian Autoencoder for Automotive Occupancy Grid Mapping**," IEEE SENSORS, 2026. doi: 10.1109/IV55156.2024.10588786.

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AE-SBL: a sparse-aware Bayesian autoencoder

Combine sparse Bayesian learning with a generative prior to reconstruct sparse maps

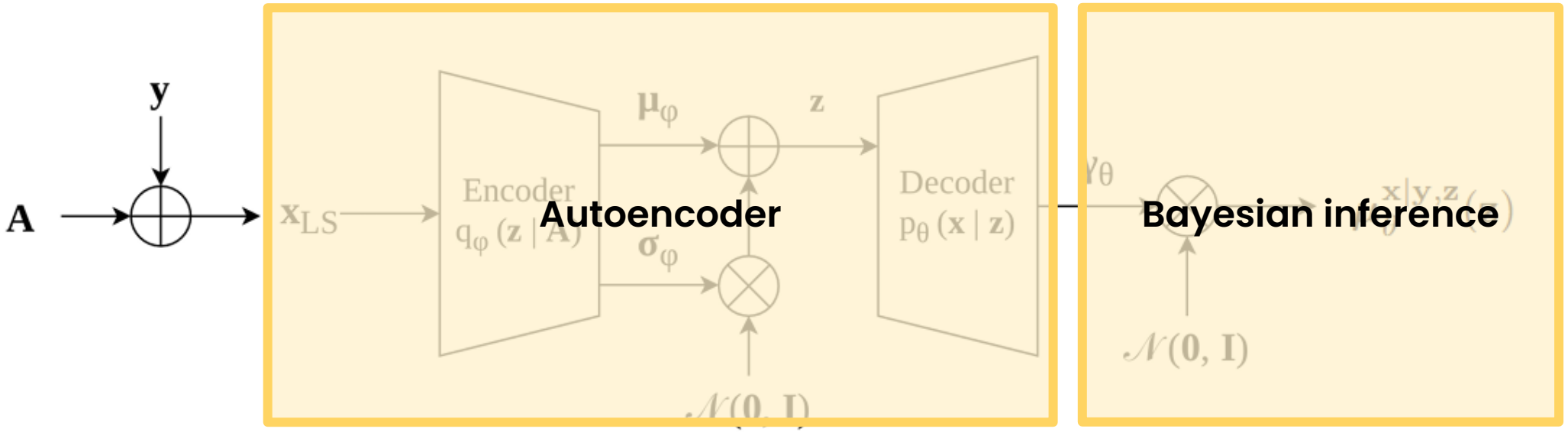


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NXP Public

AE-SBL: a sparse-aware Bayesian autoencoder

Combine sparse Bayesian learning with a generative prior to reconstruct sparse maps



"What does a plausible map look like?"

"Which map best explains the measurements while matching the learned prior?"

H. Jia et al., "**Sparse Bayesian Autoencoder for Automotive Occupancy Grid Mapping**," IEEE SENSORS, 2026. doi: 10.1109/IV55156.2024.10588786.

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Hybrid methods bridge the explicit model and learnable module

Flexible design: Many ways to integrate learning into model-based methods.



Fast inference

High data-efficiency

Better generalization

Retain physical knowledge

Next: How do we know it works? Judgement is also a bottleneck, too!

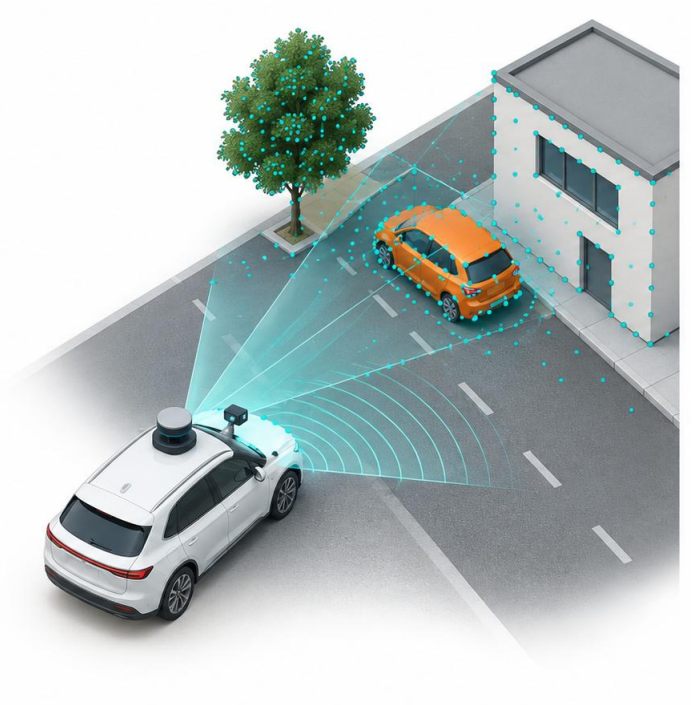
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Datasets and evaluation



What do we need in a dataset?

Sensor data



Radar LiDAR Cameras Pose

Ground truth



Obstacles

Drivable areas

Free / unknown space

Scene classes

AI-generated conceptual illustration (OpenAI).

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nuScenes

Urban driving dataset with rich modalities and annotations

Rich urban scenes

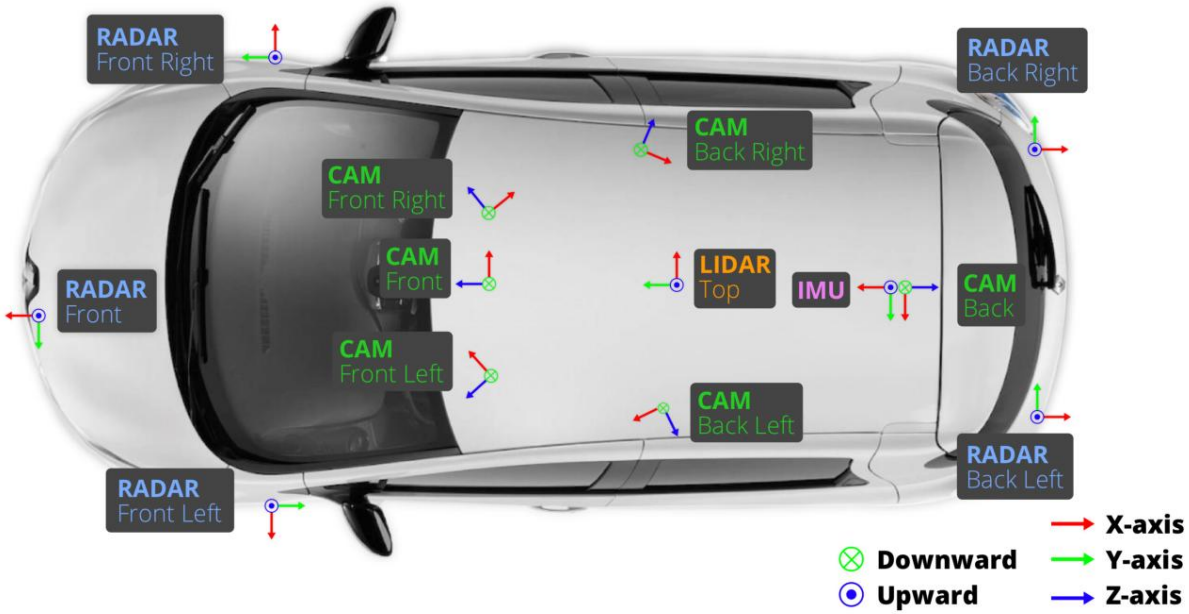
1,000 scenes, each 20 seconds of 2HZ keyframes
Boston and Singapore

Multimodal sensors

6 cameras, 5 radars
1 LiDAR with 32 beams

Reference data

3D object boxes and track IDs
Road maps
LiDAR point-level labelling



Sensors cover the area around the car

H. Caesar et al., "**nuScenes: A Multimodal Dataset for Autonomous Driving**", IEEE/CVF CVPR, 2020. DOI: 10.1109/CVPR42600.2020.01164

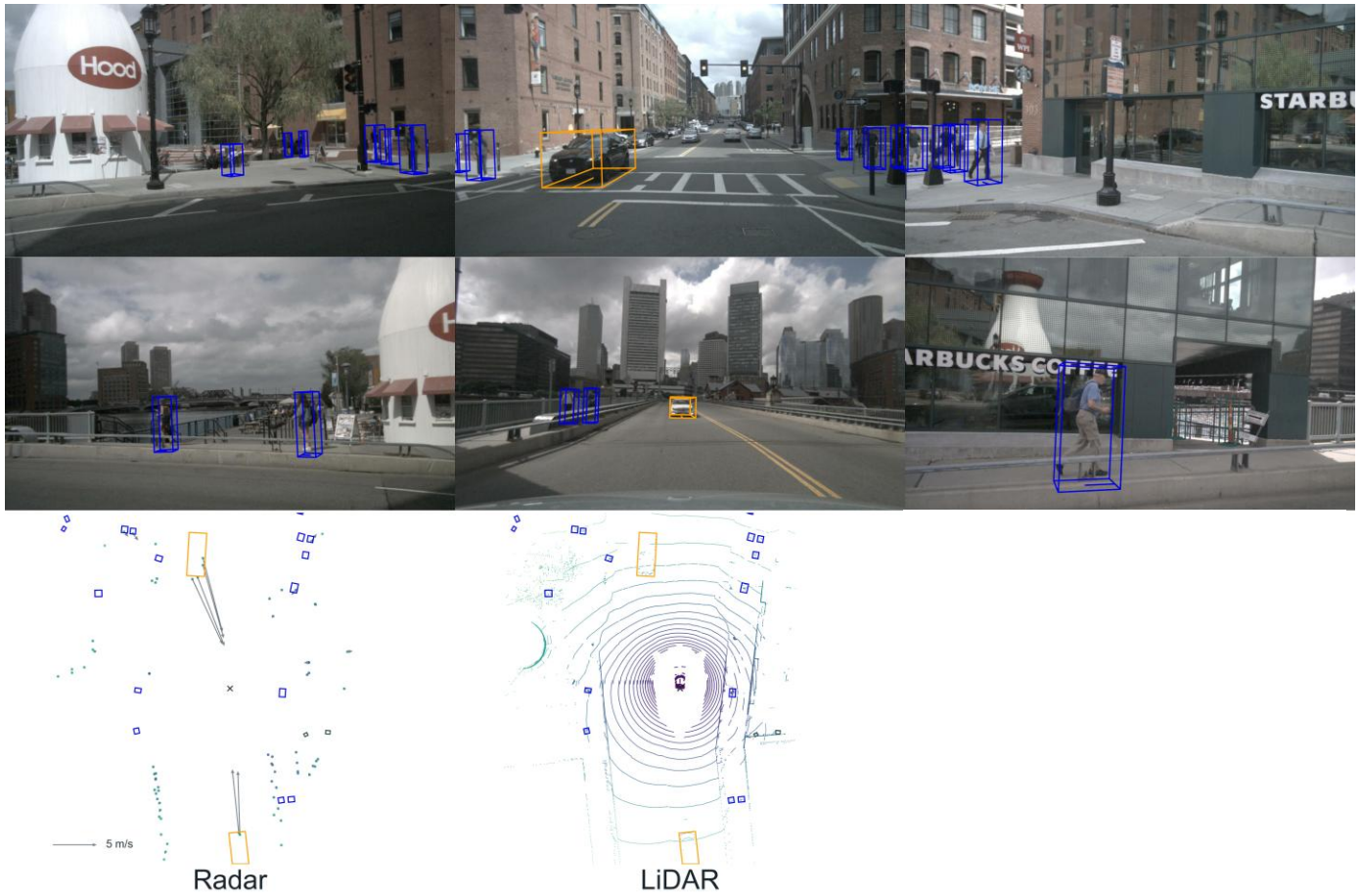
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nuScenes: data visualization and labels

Cameras Surround view

Radar Surround view 2D Doppler

LiDAR Surround view laser scan



nuScenes scene-0103: object boxes, radar motion and road map

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nuScenes: data visualization and labels

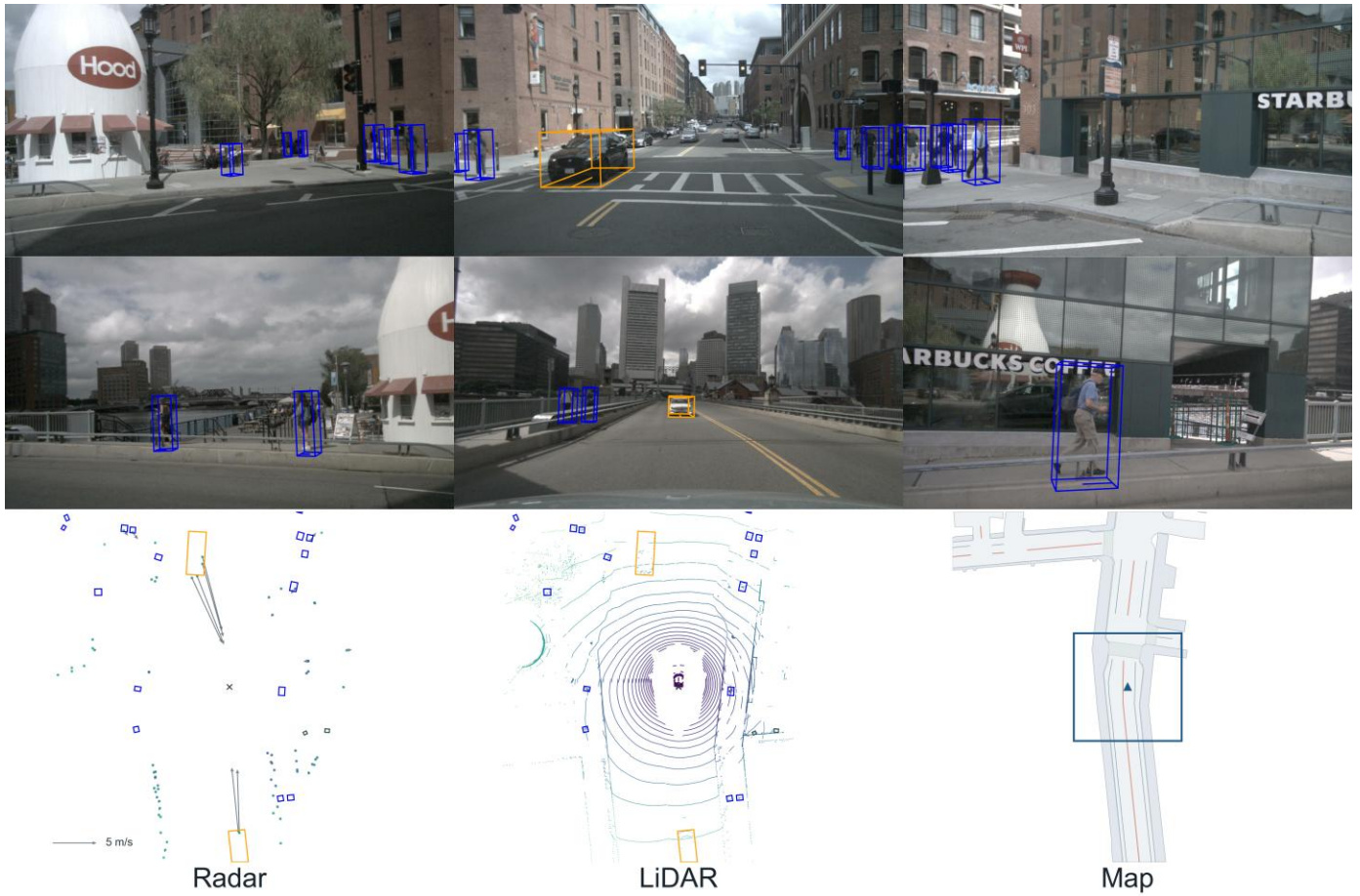
Cameras Surround view

Radar Surround view 2D Doppler

LiDAR Surround view laser scan

Ground truth boxes

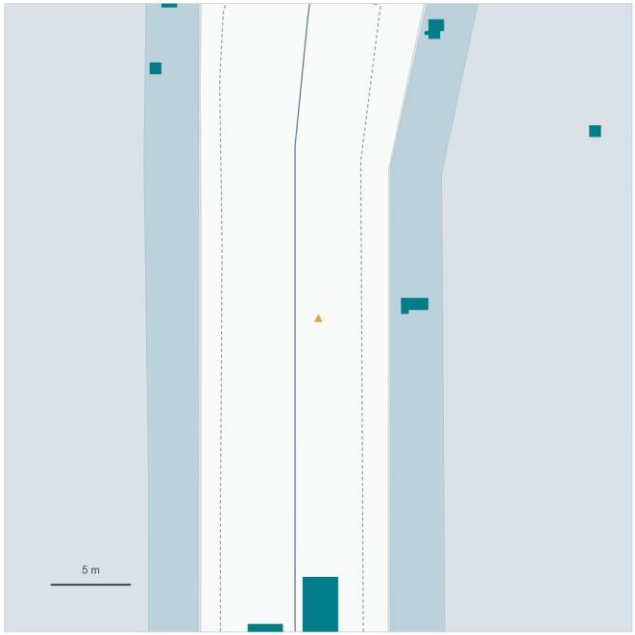
Digital map (and GPS/IMU)

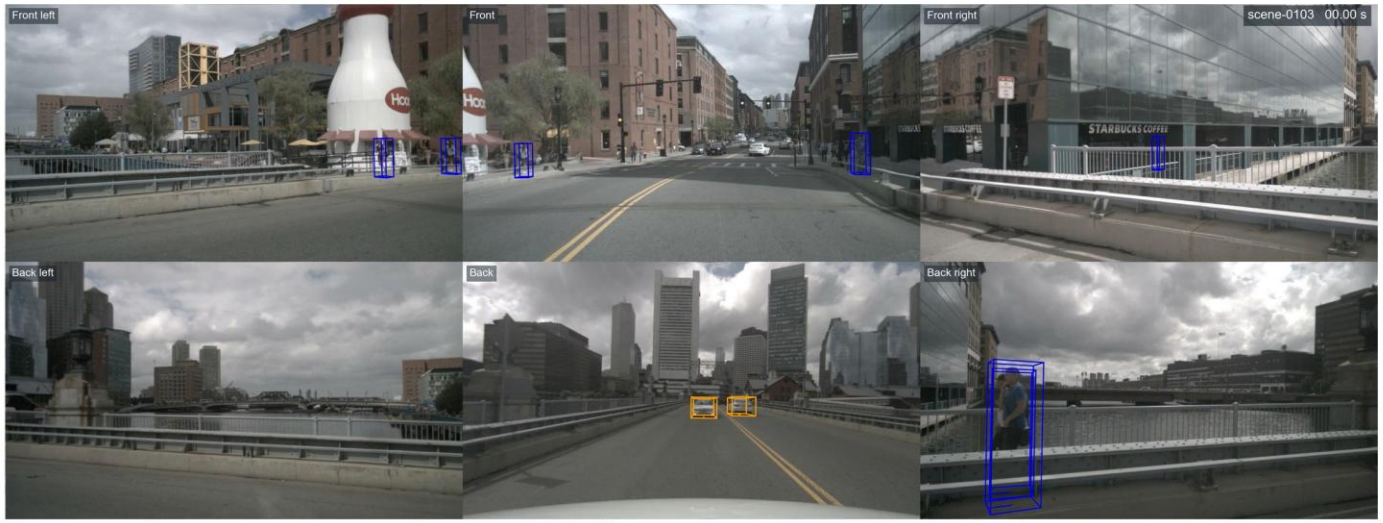


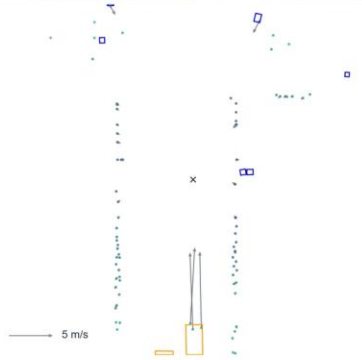
nuScenes scene-0103: object boxes, radar motion and road map

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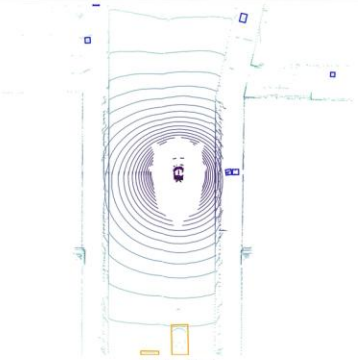
Ground truth occupancy from the dataset

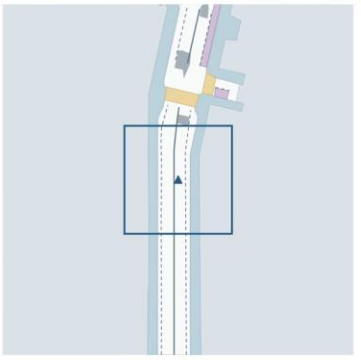






Radar


LiDAR


Digital map

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Multimodal datasets for autonomous driving

Dataset	Scale	Radar type / FoV	Radar data	LiDAR	Camera	Conditions / scenes	Provided labels / pose	Dataset task
Astyx (2019)	500 (paper)	4D radar (front)	PC + Doppler	16-ch	1 RGB		3D boxes (7 classes)	3D object detection
nuScenes (2020)	40K keyfr.	5× 2+1D (360°)	Sparse PC	32-ch	6 surround	Rain, night	3D boxes, map; lidarseg extension	Detection, tracking; LiDAR segmentation
Oxford Radar (2020)	240K scans	360° scanning radar	RA image	2×32-ch	3 mono + trinocular	Rain, fog	Radar odometry; GPS/INS, VO	Odometry / SLAM
Zendar (2020)	27 scenes	FMCW; SAR imaging	ADC, RD, PC	16-ch	1 RGB	Urban driving	Moving-car labels in RD / SAR	Moving-car detection
RADIATE (2021)	5h; 3h ann.	360° scanning radar	RA image	32-ch	Stereo	Rain, fog, snow	2D boxes (8 classes); GPS / IMU	Detection / tracking
CRUW (2021)	396K fr.	FMCW (front / side)	RA map	—	Stereo	Lighting, blur	Object centers in RA coordinates	RA object localization
CARRADA (2021)	12.7K total	FMCW (range, angle, Doppler)	RA, RD, RAD	—	1 RGB		RA / RD masks, boxes and points	Radar segmentation
RadarScenes (2021)	158 seq.	4× 2+1D (front / side)	PC + Doppler	—	1 camera	Rain included	Point labels + IDs (11 moving classes)	Point segmentation; tracking
RADIal (2022)	25K total	4D HD radar (front)	ADC; RD / PC*	16-ch	1 RGB	Urban / rural / highway	Image boxes + range; camera-derived free mask	Detection / free space
View-of-Delft (2022)	8,693 ann.	3+1D radar (front)	PC + Doppler	64-ch	Stereo	Urban traffic	3D boxes + IDs; pose	3D road-user detection
Radatron (2022)	152K total	4D cascade (front)	High-res RA	—	Stereo	Controlled fog	Vehicle boxes in radar BEV	Radar vehicle detection
K-Radar (2022)	35K fr.	4D imaging (front)	4D tensor; PC*	64/128-ch	4 stereo pairs	Rain, fog, snow	3D boxes + track IDs	3D object detection
RaDelft (2024)	16,975 fr.	4D cascade (front)	ADC, RAD, PC	128-ch	1 camera	Delft urban / suburban	LiDAR-derived boxes; per-point class labels	Radar detection
OmniHD-Scenes (2026)	450K+ fr.	6× 4D radar (360°)	4D PC	128-ch	6 surround	Rain, night	3D boxes, IDs; semantic occupancy	3D detection / semantic occupancy

2+1D = range / azimuth + Doppler; 4D adds elevation. ADC = raw samples; RA / RD / RAD = radar maps / tensors; PC = point cloud.
Scale units differ; ann. = annotated. *Processed from radar data. Full references: the reference page.

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Multimodal datasets for autonomous driving

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CRUW (2021)	396K fr.	FMCW (front / side)	RA map	—	Stereo	Lighting, blur	Object centers in RA coordinates	RA object localization
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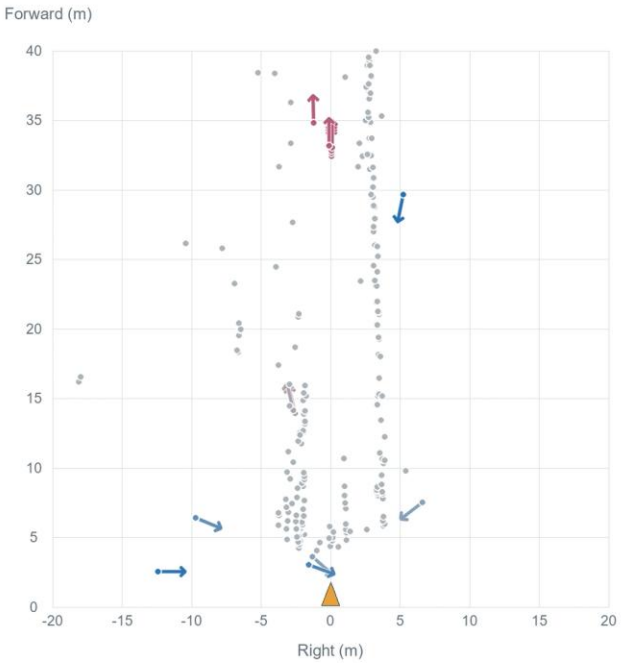
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View-of-Delft

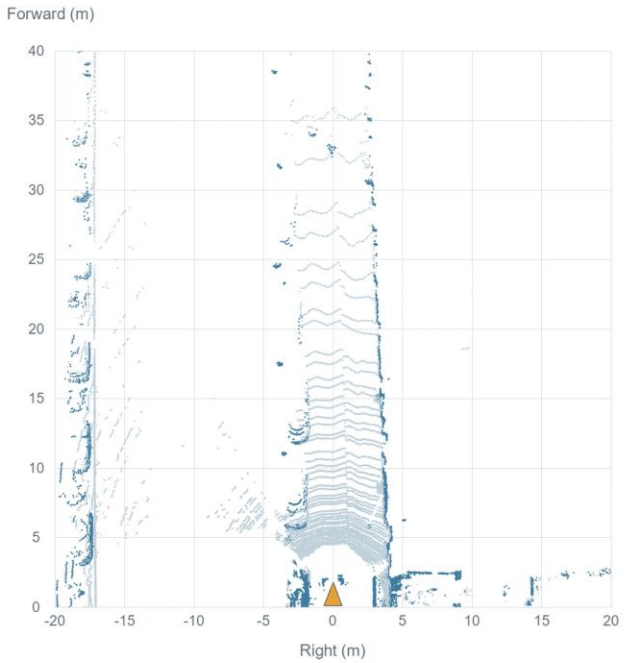
3D + 1 Doppler radar and many vulnerable road users



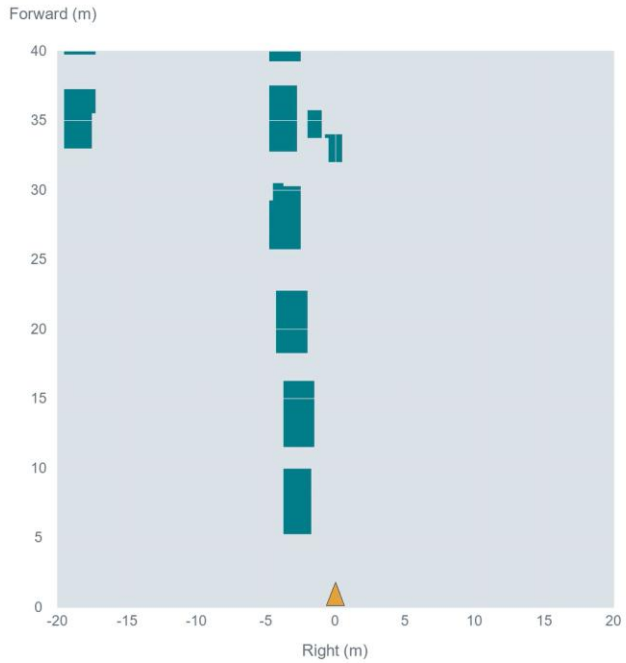
Camera



Radar



LiDAR



Occupancy

A. Palffy et al., "**Multi-Class Road User Detection With 3+1D Radar in the View-of-Delft Dataset**," IEEE RA-L, 2022. doi: 10.1109/LRA.2022.3147324.

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Multimodal datasets for autonomous driving

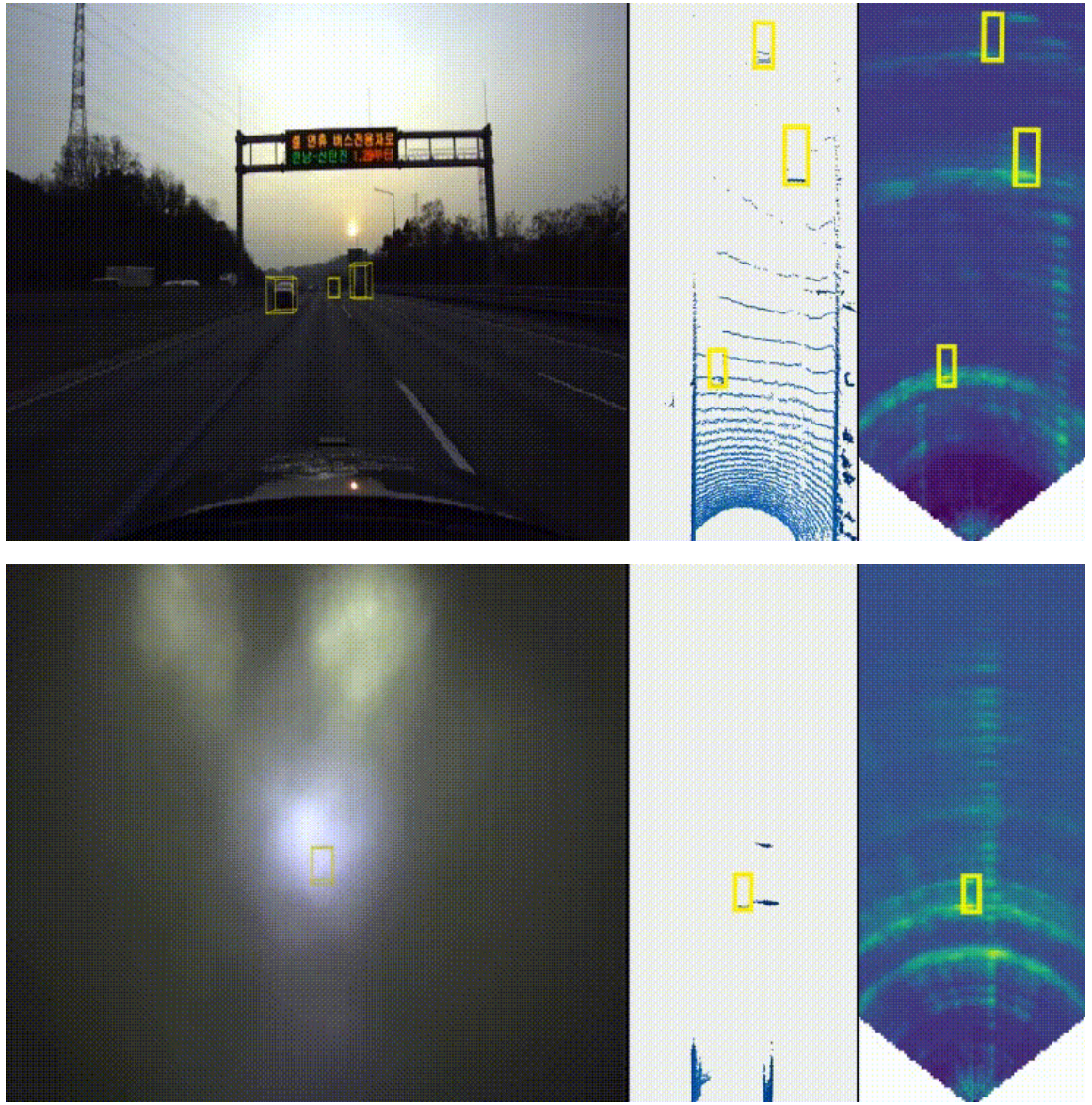
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NXP Public

K-Radar

Rich scenes with many adverse weather sequences



D.-H. Paek et al., "**K-Radar: 4D Radar Object Detection for Autonomous Driving in Various Weather Conditions**," NeurIPS, 2022. doi: 10.52202/068431-0276.

NXP Public

Multimodal datasets for autonomous driving

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Scale units differ; ann. = annotated. *Processed from radar data. Full references: the reference page.

Many outdoor datasets are available, how about indoor?

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Indoor and robot datasets for occupancy studies

There are some indoor datasets appearing.

Dataset	Scale / coverage	Platform / scenes	Sensor inputs*	Provided reference	Occupancy use
UTIn3D (2023)	2 indoor areas One building	Ground robot People and furniture	3D LiDAR	Automatic point labels SLAM poses	Derive 2D grid targets with obstacle classes
M2DGR (2022)	36 sequences Indoor / outdoor	Ground robot Rooms, halls, lifts	3D LiDAR Cameras, IMU	Motion capture / tracker RTK poses outdoors	Build indoor maps Create grid labels
SubT-MRS (2024)	Multiple sites Indoor / outdoor	Several platforms Halls, caves, stairs	LiDAR, cameras, IMU Varies by sequence	Surveyed 3D maps Map-based poses	Grid targets from maps Ignore unseen cells
ColoRadar (2022)	52 sequences 145+ min, mixed	Carried sensor rig Halls, labs, mines	2 radars, 3D LiDAR IMU	LiDAR-SLAM poses Motion capture in ASPEN	Study radar mapping Build LiDAR references
OpenLORIS (2020)	22 sequences 5 indoor scenes	Ground robot Office, home, market	LiDAR, cameras IMU, wheel odometry	Office: motion capture Other: laser-map poses	Study changes over visits Create grid labels
NCLT (2016)	27 sessions 15 months, mixed	Segway robot Buildings and campus	3D / 2D LiDAR IMU, cameras, wheels	SLAM reference poses GPS helps outdoors	Study repeated mapping Create grid labels
Hilti-Oxford (2023)	Construction sites	Handheld rig Indoor / outdoor	3D LiDAR Cameras, IMU	Surveyed laser scans Position / pose reference	Derive geometry targets Choose grid and masks

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Indoor and robot datasets for occupancy studies

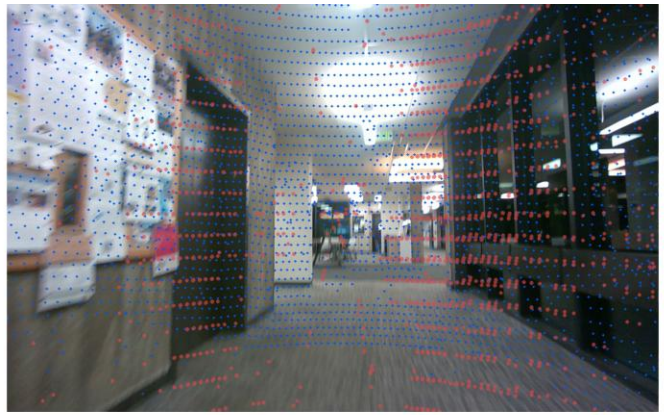
There are some indoor datasets appearing.

Dataset	Scale / coverage	Platform / scenes	Sensor inputs*	Provided reference	Occupancy use
UTIn3D (2023)	2 indoor areas One building	Ground robot People and furniture	3D LiDAR	Automatic point labels SLAM poses	Derive 2D grid targets with obstacle classes
M2DGR (2022)	36 sequences Indoor / outdoor	Ground robot Rooms, halls, lifts	3D LiDAR Cameras, IMU	Motion capture / tracker RTK poses outdoors	Build indoor maps Create grid labels
SubT-MRS (2024)	Multiple sites Indoor / outdoor	Several platforms Halls, caves, stairs	LiDAR, cameras, IMU Varies by sequence	Surveyed 3D maps Map-based poses	Grid targets from maps Ignore unseen cells
ColoRadar (2022)	52 sequences 145+ min, mixed	Carried sensor rig Halls, labs, mines	2 radars, 3D LiDAR IMU	LiDAR-SLAM poses Motion capture in ASPEN	Study radar mapping Build LiDAR references
OpenLORIS (2020)	22 sequences 5 indoor scenes	Ground robot Office, home, market	LiDAR, cameras IMU, wheel odometry	Office: motion capture Other: laser-map poses	Study changes over visits Create grid labels
NCLT (2016)	27 sessions 15 months, mixed	Segway robot Buildings and campus	3D / 2D LiDAR IMU, cameras, wheels	SLAM reference poses GPS helps outdoors	Study repeated mapping Create grid labels
Hilti-Oxford (2023)	Construction sites	Handheld rig Indoor / outdoor	3D LiDAR Cameras, IMU	Surveyed laser scans Position / pose reference	Derive geometry targets Choose grid and masks

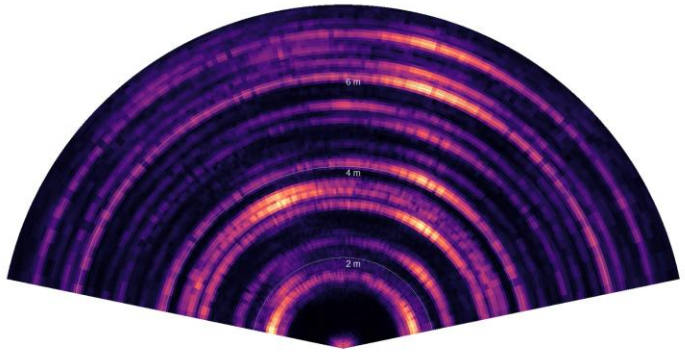
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ColoRadar

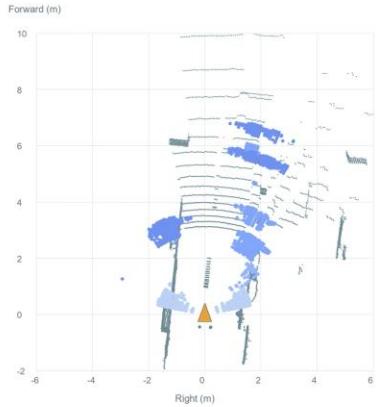
An indoor dataset with radar, LiDAR, camera



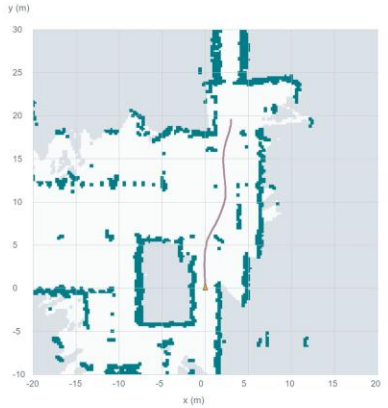
Camera



Radar intensity



LiDAR and radar



Pseudo-occupancy ground truth

Indoor datasets exists,
but we still need better radar and annotations.

A. Kramer et al., "**ColoRadar: The direct 3D millimeter wave radar dataset**," The International Journal of Robotics Research, 2022. doi: 10.1177/02783649211068535.

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Indoor and robot datasets for occupancy studies

There are some indoor datasets appearing.

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Indoor datasets with better radar and annotations are needed.

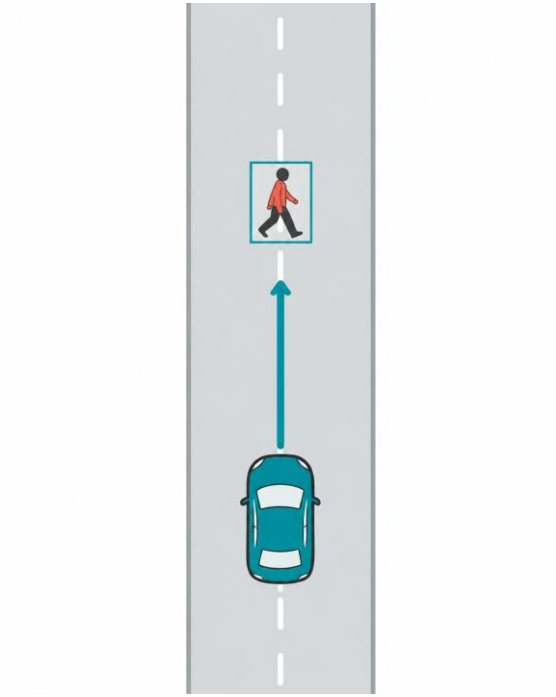
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After we have data

The methods need evaluation in several aspects.

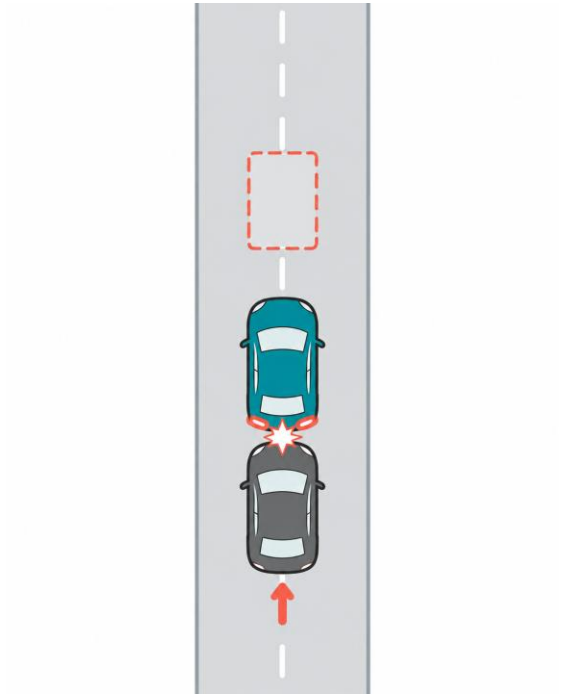
Good obstacle detection

Where should we not drive into?



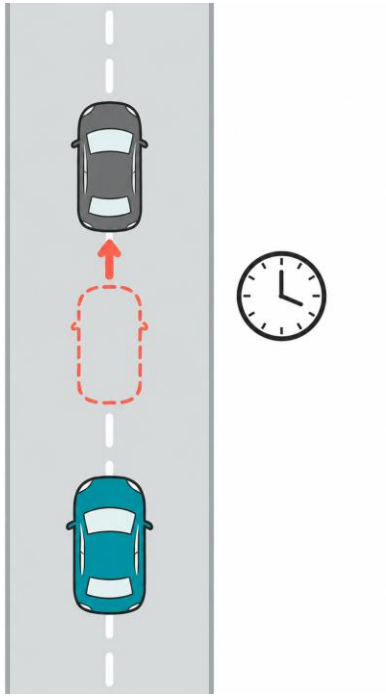
Good free space detection

Phantom braking can be dangerous.



Realtime

Perception should be fast enough.



AI-generated conceptual illustration (OpenAI).

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Evaluation metrics

IoBB and detection

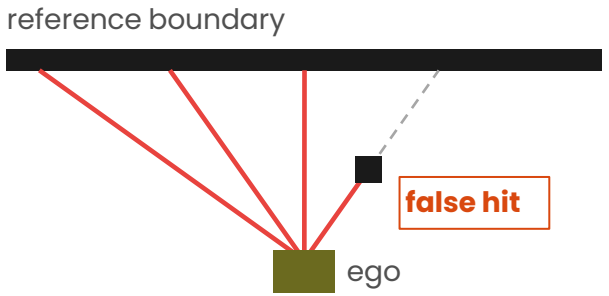


Detection rate: 1 of 2 targets

Box coverage and targets found

Higher is better

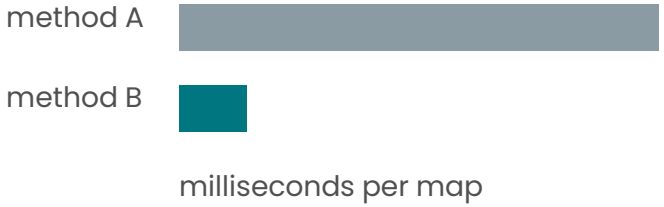
AS-NMSE



First occupied boundary

Lower is better

Runtime



Milliseconds per map

Lower is better

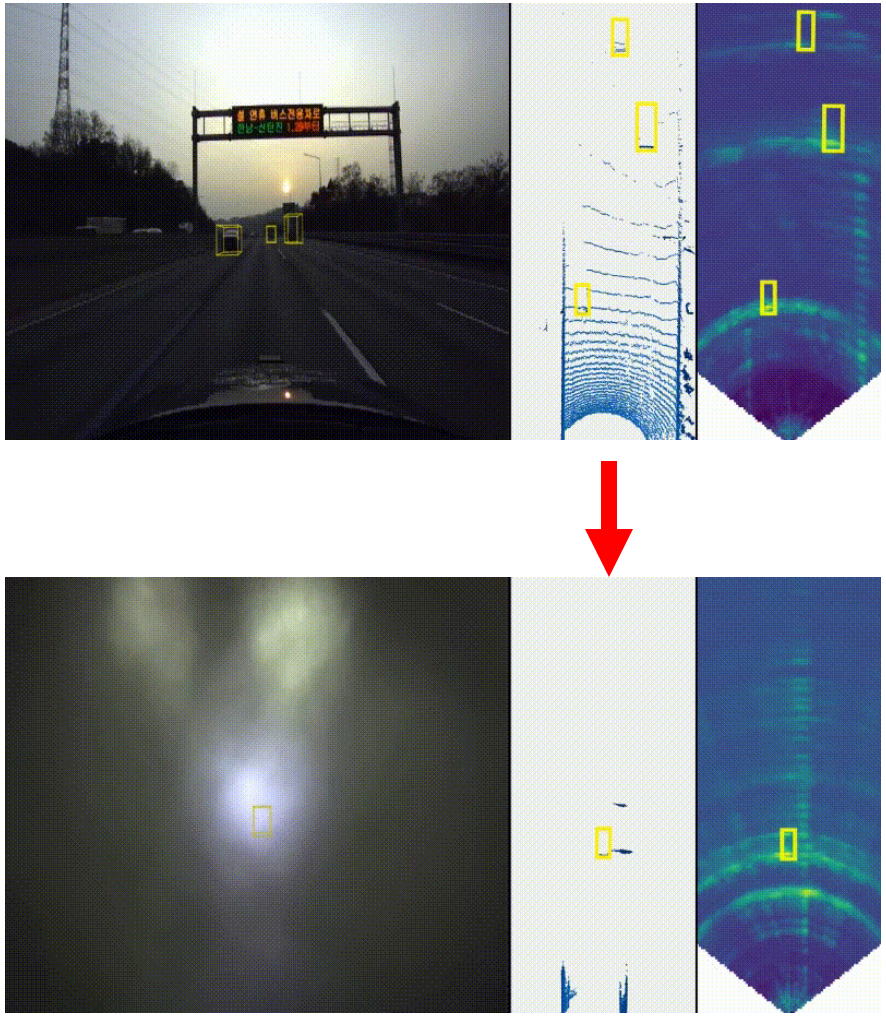
Ç. Önen et al., "**Occupancy Grid Mapping for Automotive Driving Exploiting Clustered Sparsity**," IEEE Sensors J., 2024. doi: 10.1109/JSEN.2023.3342463.

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How these metrics reflect the mapping quality

LiDAR perception ability drops in snowy weather, giving worse map

Example from K-Radar



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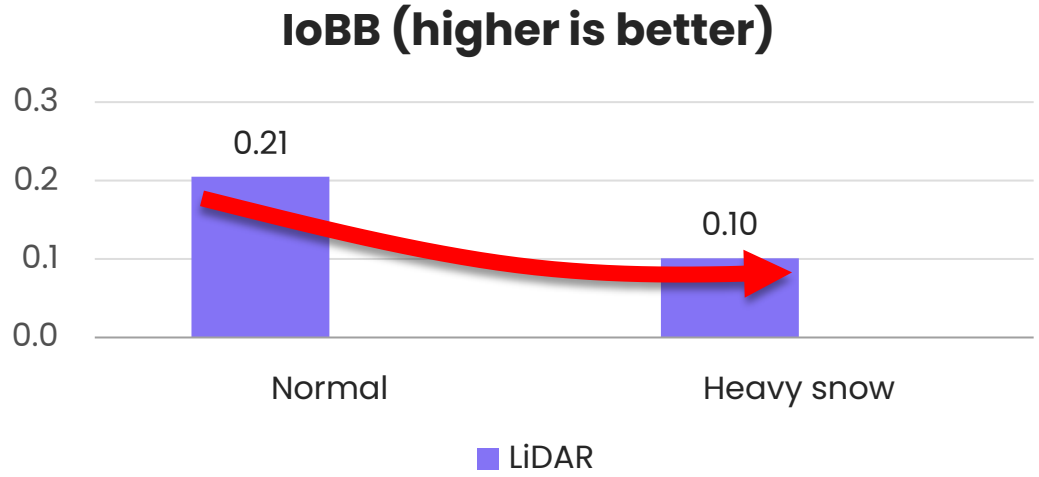
How these metrics reflect the mapping quality

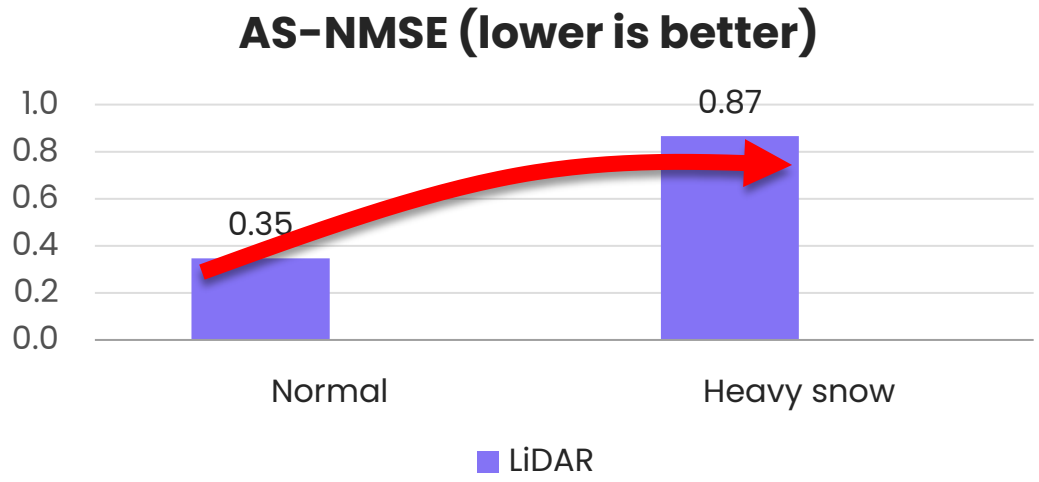
LiDAR perception ability drops in snowy weather, giving worse map

This change can be reflected by error metrics:

Lower IoBB → Worse detection

Higher AS-NMSE → More free-space error



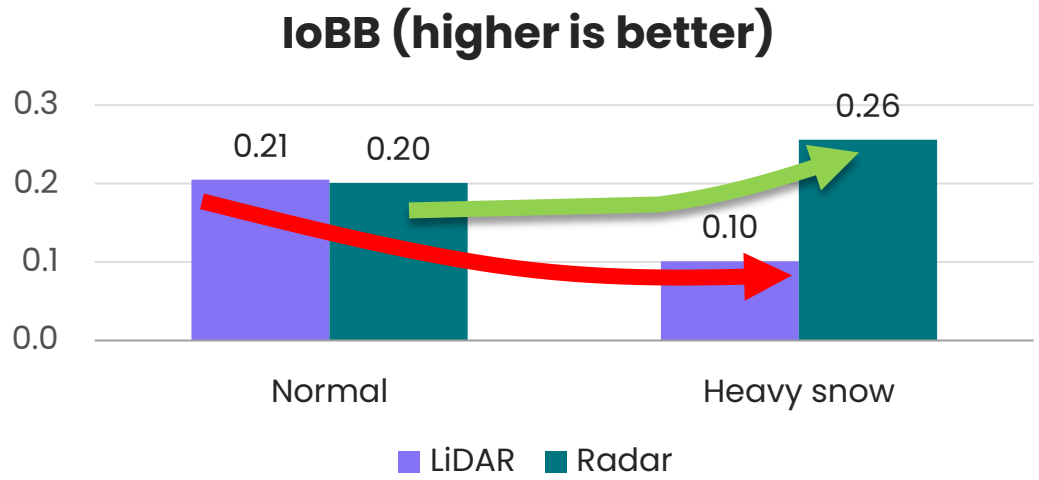


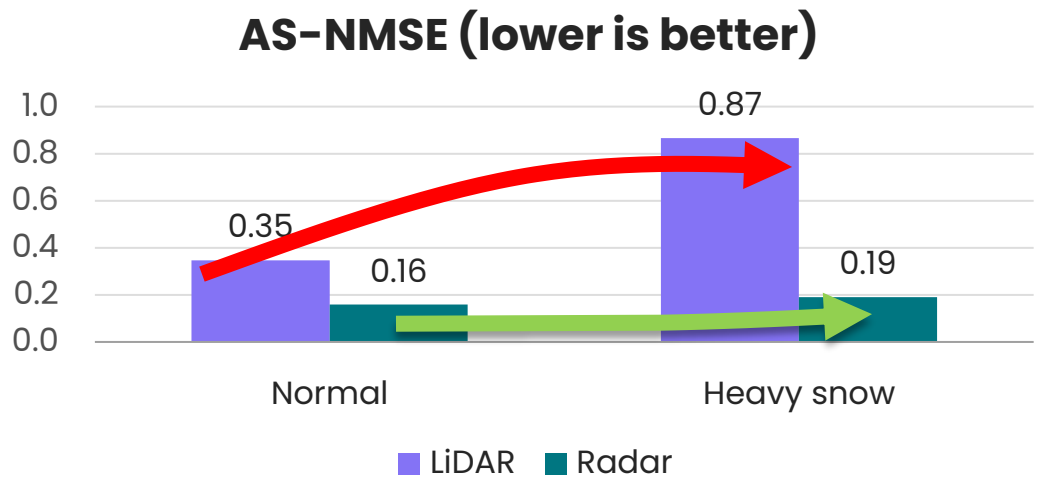
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How these metrics reflect the mapping quality

Radar and LiDAR in snowy weather

Radar is more robust in this heavy snow example, as reflected by the metrics.





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Performance analyzed with all metrics



≈186× faster

Autoencoder vs Bayesian

Mapping quality and speed matter together

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Datasets and evaluation

Match the application	Choose sensors and scenes that fit the intended use.
More indoor datasets needed	Many outdoor datasets are available. More indoor datasets are needed.
Evaluation in multiple aspects	Assess multiple metrics for comprehensive performance evaluation.

Next: Key takeaways and further directions in occupancy mapping

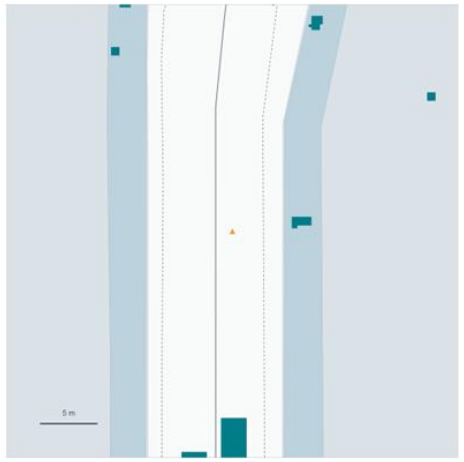
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Summary and extensions



Key messages

One shared map



Sensing Planning Control

Give sensing, planning and control the same view of the environment.

Hybrid methods: a promising direction

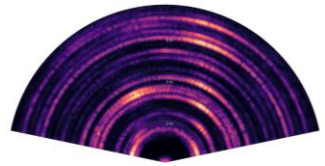
Physical knowledge + **Learning**

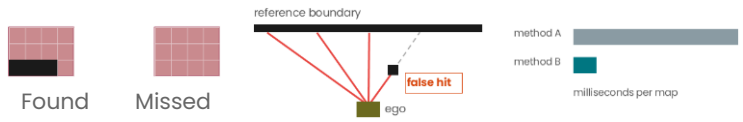
Hybrid occupancy mapping

Keep useful physical models.
Learn what is hard to describe.

Test what matters







Obstacles Free space Time

We need more datasets for indoor robotics.
Evaluate map quality and processing time.

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Further directions in occupancy mapping

3D and semantics

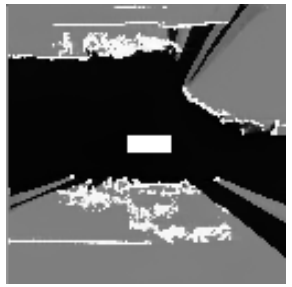


Height and object classes

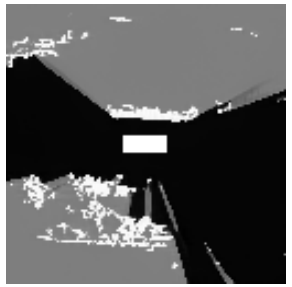
3D cells show shape.
Colours show classes.

RadarOcc

Motion and forecasting



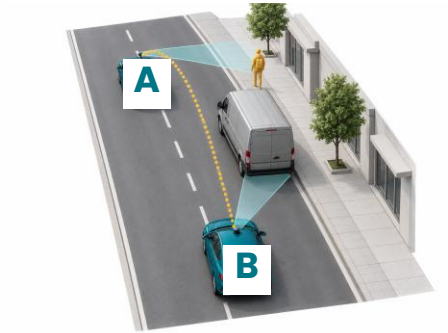
In 0.5 s



In 3 s

Predict future occupied space

Cooperative mapping



Share a view behind an obstacle

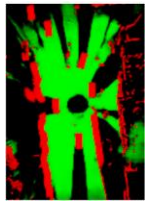
A sees the pedestrian.
The van blocks B's view.

Cooperative scene: AI-generated illustration (OpenAI)

Simulation and real data



Simulated labels



Real LiDAR test

Train in simulation. Test on real data.

EviLOG

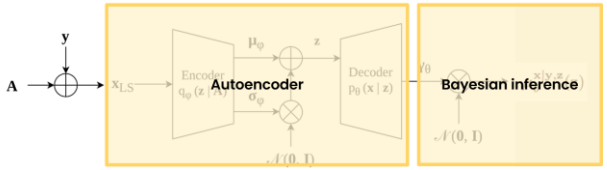
Green: free Red: occupied Black: unknown

F. Ding et al., "**RadarOcc: Robust 3D Occupancy Prediction with 4D Imaging Radar**", NeurIPS, 2024. doi: 10.52202/079017-3222.
B. Lange et al., "**LOPR: Latent Occupancy PRediction using Generative Models**", arXiv, 2022. doi: 10.48550/arXiv.2210.01249.
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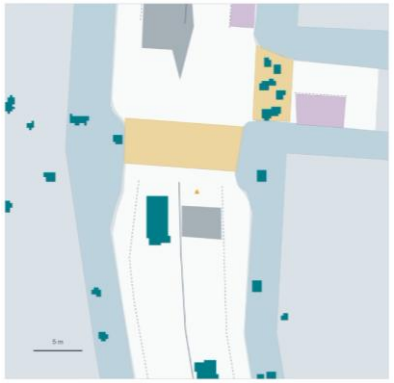
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OGM: A core perception block
Autonomous driving and robotics navigation

Physics-based learning



Labeled datasets… Robotics



Application-specific metrics



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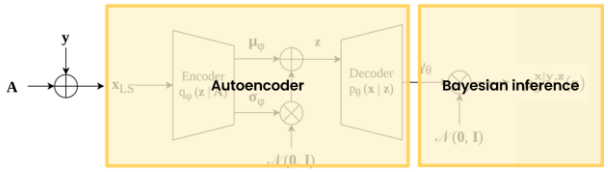
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OGM: A core perception block
Autonomous driving and robotics navigation

Physics-based learning



Labeled datasets… Robotics



Application-specific metrics



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Ashish Pandharipande	ashish.pandharipande@nxp.com

Coming days

A4L-A, Lecture, *Van Oldenbarnevelt*
26 Oct (Monday) 16:00-17:00

B4L-E, Lecture, *Mees II*
27 Oct (Tuesday) 16:00-17:00

H. Jia et al., "**Autoencoder-Enhanced Sparse Bayesian Learning for Efficient Automotive Occupancy Grid Mapping**"

P. Zhai et al., "**Radar-Based Sparsity-Aware Dynamic Occupancy Grid Mapping**"

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