

Virtual Testing of Automotive LiDAR

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Overview

- Introduction
- Blickfeld's Perspective on the Automotive Sensors
- Importance of Sensor Placement
- Sensor Modelling for Use-Case Analysis: Geometric Considerations
- Physical LiDAR Sensor Model
- Validation
- Outlook

VIVALDI Project Key Objectives



Virtual Verification & Validation

How safe is safe enough?

How realistic is realistic enough?

- **Fidelity metrics** of simulation and test chains
- **Complementary methods** from simple to realistic: SiL, HiL, ViL, FoT
- **Multi-sensor platforms:** RADAR + LiDAR + Camera
- **Open interfaces:** Scenario generation, sensor and environmental models, co-simulation
- **Knowledge base** created from a reference architecture

- *VIVALDI* – Virtual Validation Tool Chain for Automated and Connected Driving
- *SiL* – Software in the loop
- *HiL* – Hardware in the loop
- *ViL* – Vehicle in the loop
- *FoT* – Field-operational test

Source: Prof. Matthias Hein TU Ilmenau

Blickfeld & UAS Kempten: Objectives in VIVALDI



- **Development** of physical LiDAR sensor behavioral models using standardized interfaces
 - Open Simulation Interface (OSI)
 - Functional Mockup Interface (FMI)

- **Focus** on environmental modelling:
 - The virtual test chain will be strengthened by experiences with "digital twins", Kempten city model
 - Real world scenarios to be implemented in standardized formats like OpenDRIVE and OpenSCENARIO

- **Development** of the metrics to validate the similarity between the LiDAR model and real measurement at the point cloud level

Blickfeld 3D LiDAR Systems for Intelligent Environment Perception



Facts & Figures

Foundation: 2017
Headquarter: Munich, Germany
International: Palo Alto, USA
Distributor network: Germany, Switzerland, Spain, Norway, USA, China, Japan, S.Korea, India, Singapore, Malaysia, Vietnam, Thailand, Indonesia

Core assembly locations: Germany, Singapore

Certifications: ISO9001



Product Portfolio

IoT business		Automotive	
Cube 1		Vision Plus	
Cube Range 1		Vision Mini	
Software Stack		MEMS Scanning Module 118 (BDU)	

Breakthrough technology

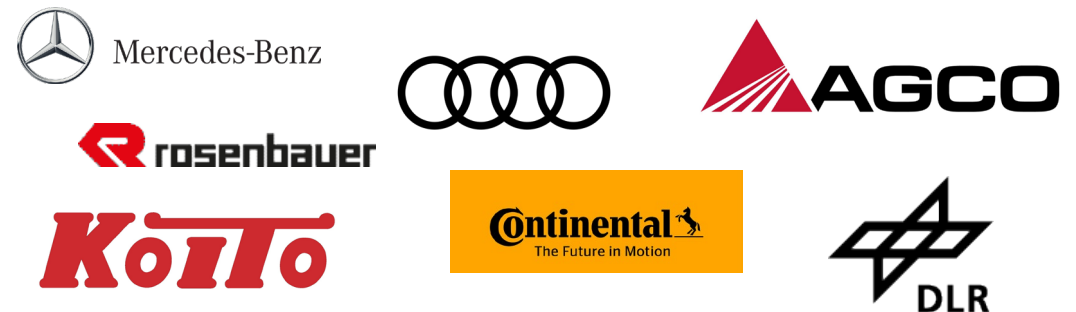


13
Innovation Awards

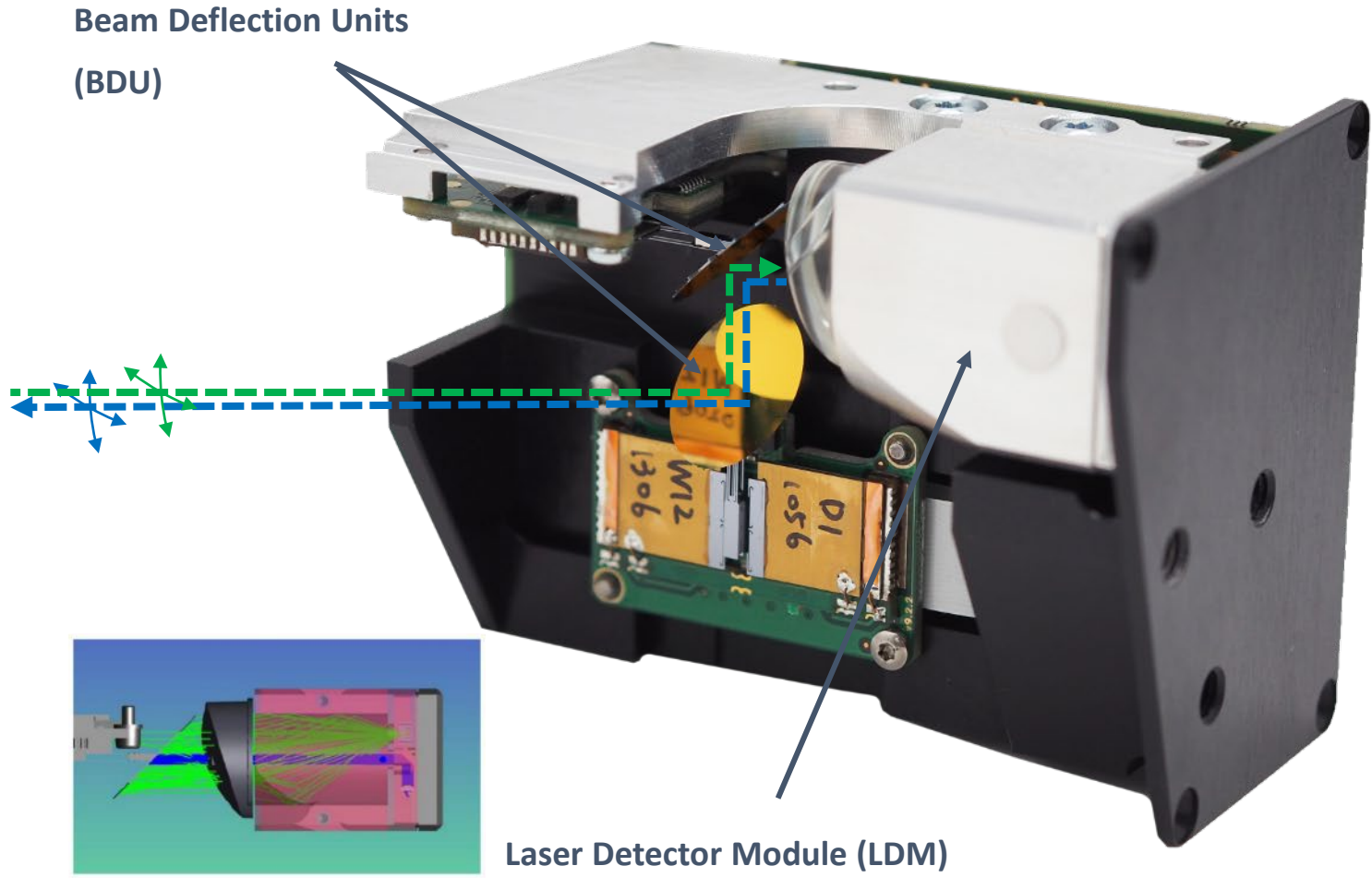


60+
Patents

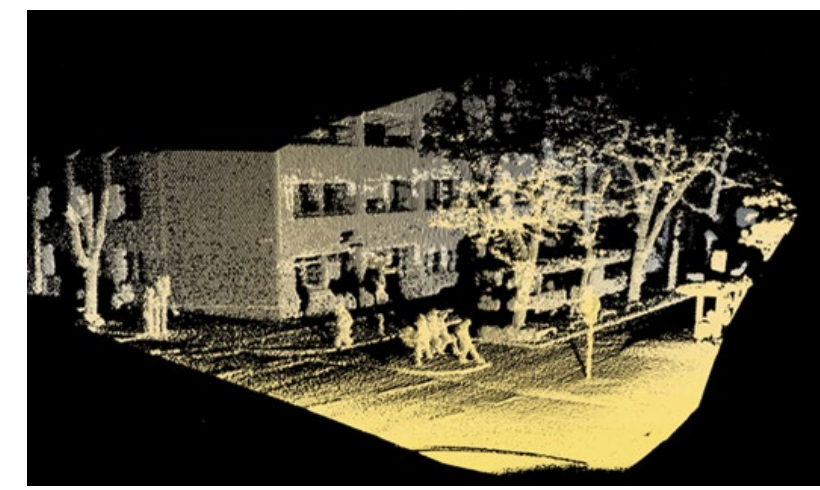
Selected automotive customers & research partners



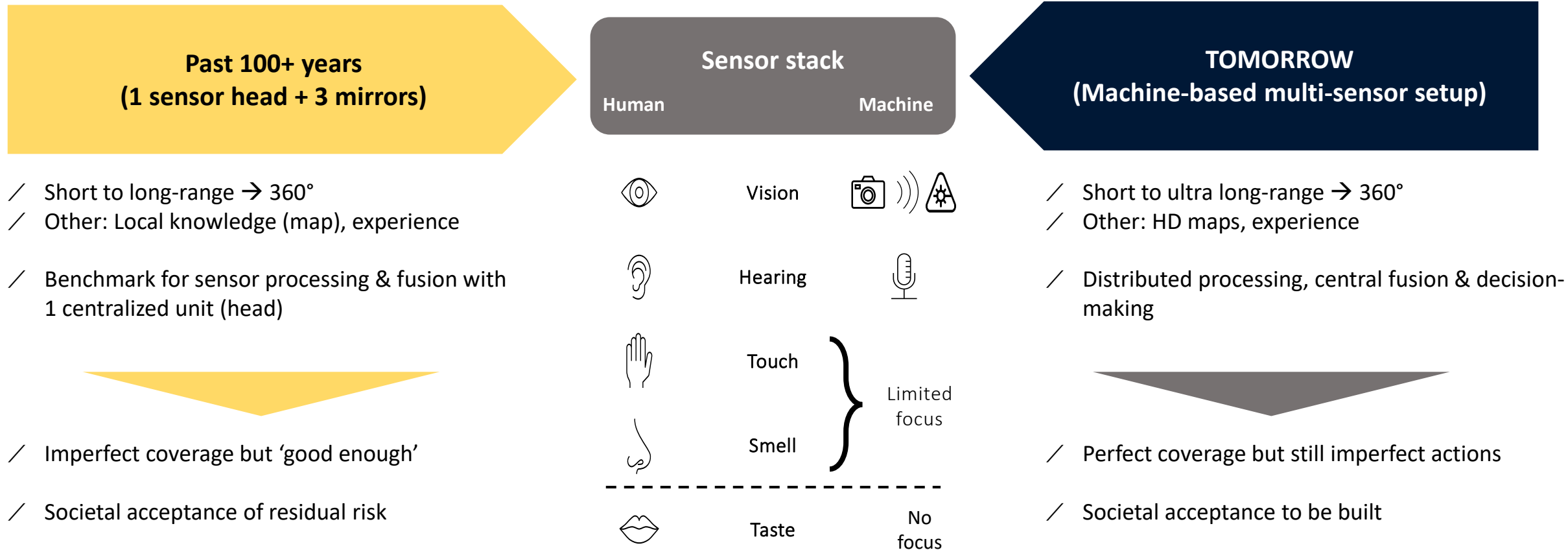
Blickfeld LiDAR Technology



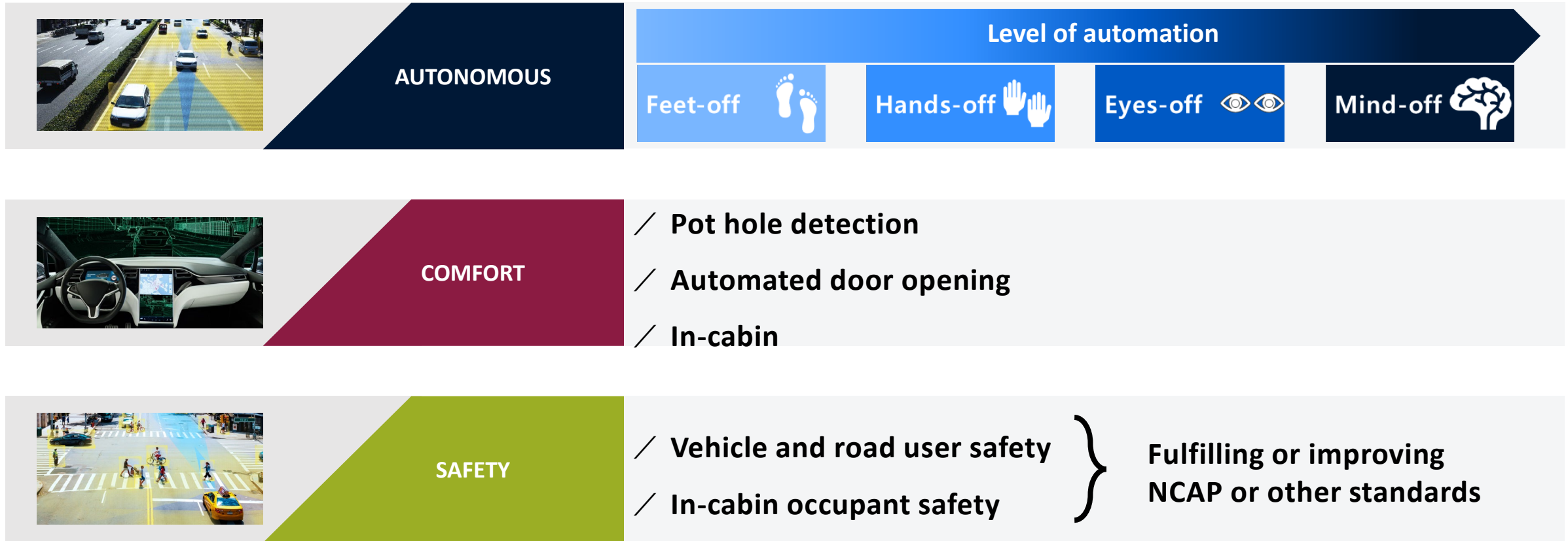
Exemplary 3D point cloud



100+ years automotive with 1 sensor head and 3 mirrors will...
 ...@transform to an entirely new level in the next years



Machine sensors, esp. LiDAR, can do more than humans...
 ... @ higher reliability



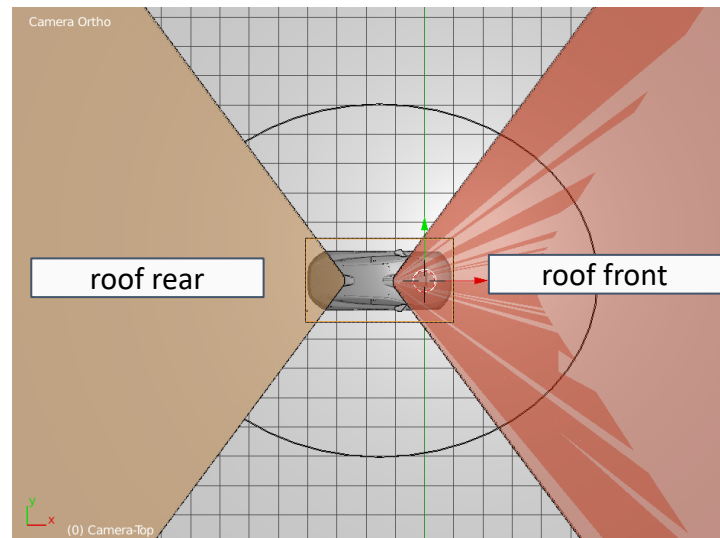
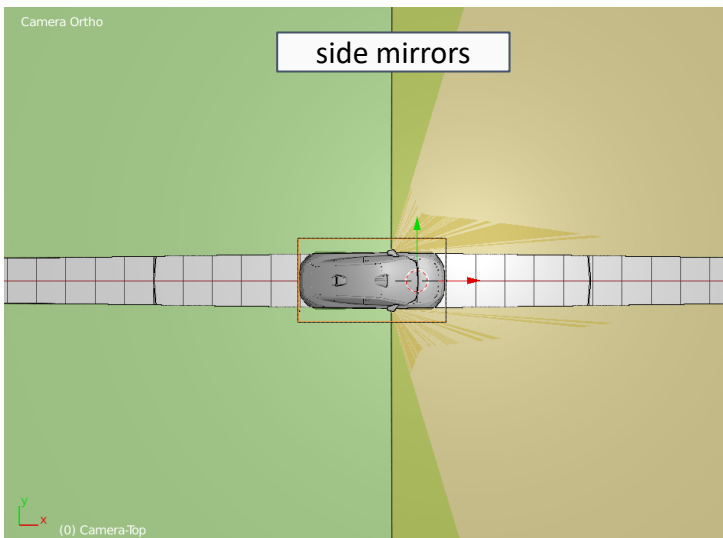
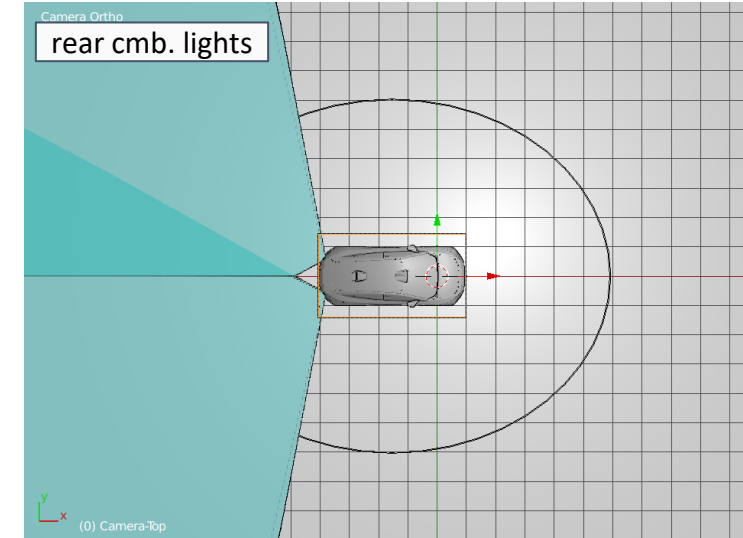
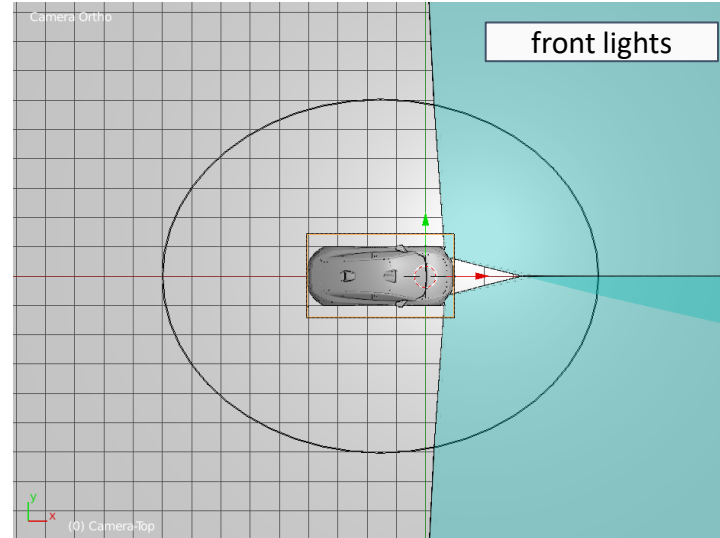
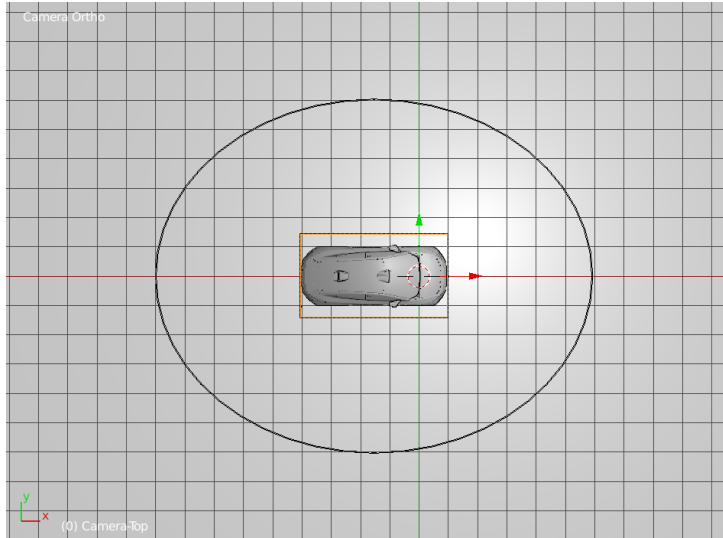
Surround View (Cocooning) Required For AD

Exemplary use cases - URBAN -		Long-range (front & rear) ¹⁾	Cocooning (surround view) ²⁾	
Vehicle starts driving		X	X	
Exemplary use cases - RURAL -		Long-range (front & rear) ¹⁾	Cocooning (surround view) ²⁾	
Road crossing	Cruise up to 100km/h	X		
Exemplary use cases - HIGHWAY -		Long-range (front & rear) ¹⁾	Cocooning (surround view) ²⁾	
Emergency Traff	Overtaking mult	Cruise (same lane) up to 130km/h	X	
		Lane change, merge or extension (e.g. 2 to 3 lanes or 3 to 2 lanes)	X	X
R	Lane chang	Overtaking manoeuvre	X	X
		Evasive manoeuvre (e.g. object falling of a vehicle)	X	X
R	R	Emergency braking (e.g. due to accident or tail end of traffic jam)	X	X
		Ramp-on / off	X	X
		Traffic jam (incl. vehicle start after longer stop & emergency lane)		X
		Roadworks (e.g. reduced lane width)	X	X
		Obstructions (e.g. accident site, wrong	X	X

1) Long-range up to 300m and high resolution (potential sensors: RADAR, Camera, LiDAR), front-facing includes also rear-facing long-range

2) Short-medium range up to 150m detection of vehicles (potential sensors: RADAR, Camera, LiDAR, Ultrasound)

Surround View: Coverage



✓ Passenger cars the most challenging case due to complicated geometry and design considerations (compared to shuttles and trucks)

In collaboration with Genesis Design



Surround View

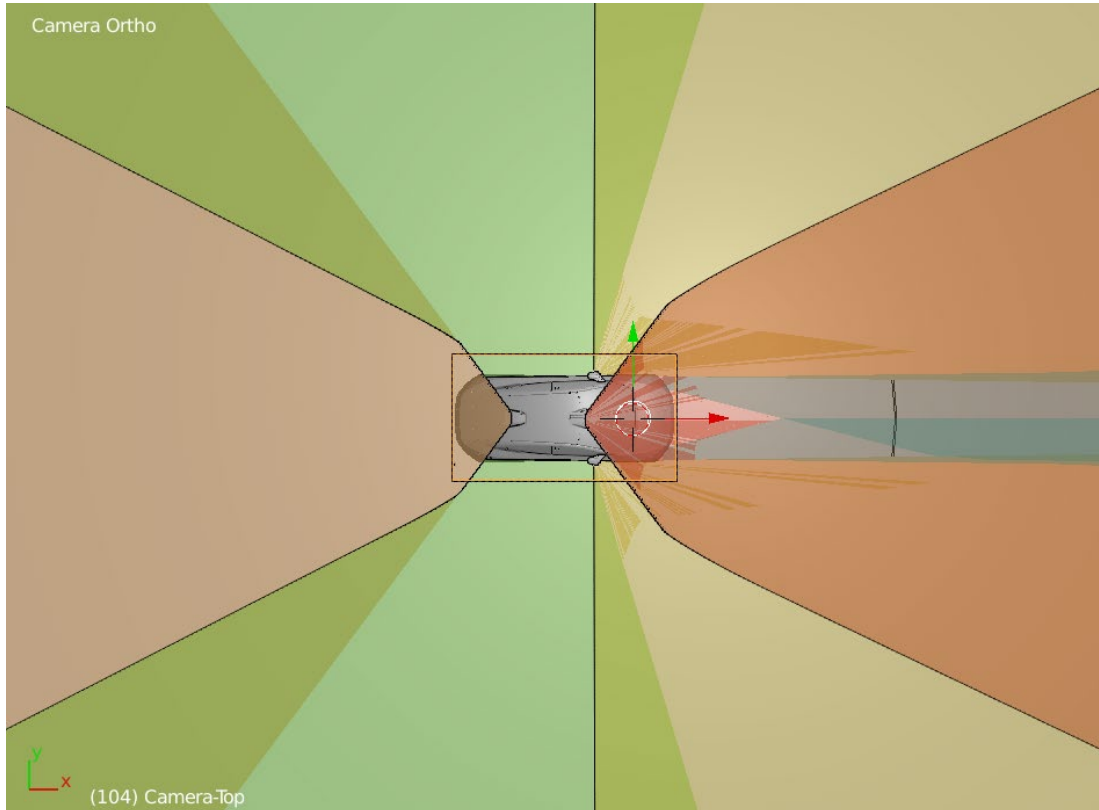


In collaboration with Genesis Design

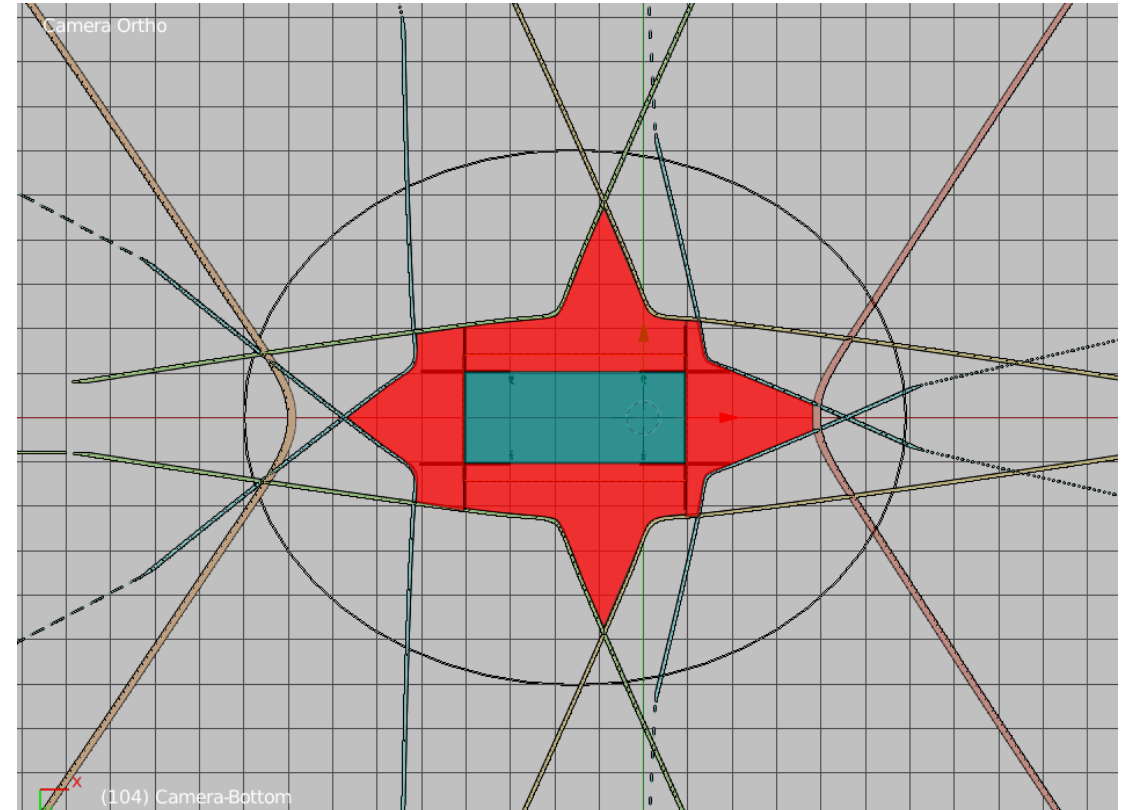


Surround View: Coverage

top view



bottom view

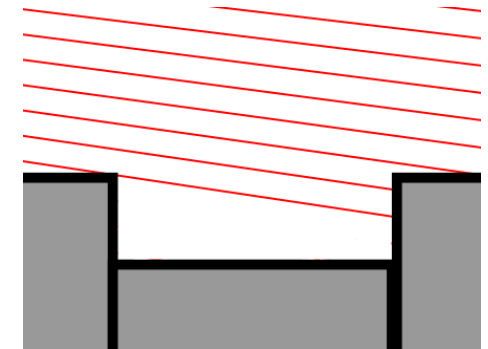
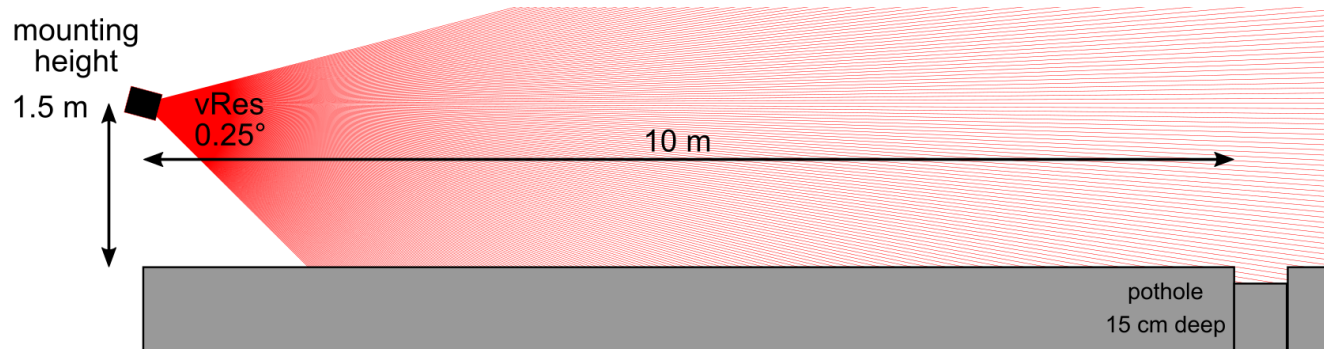


In collaboration with Genesis Design

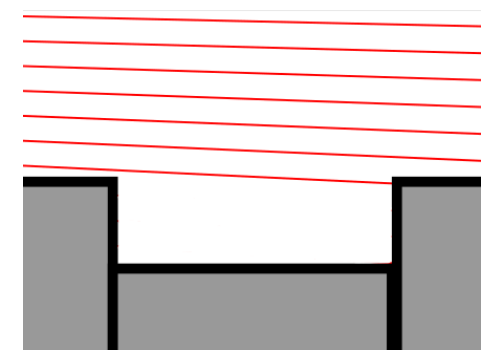
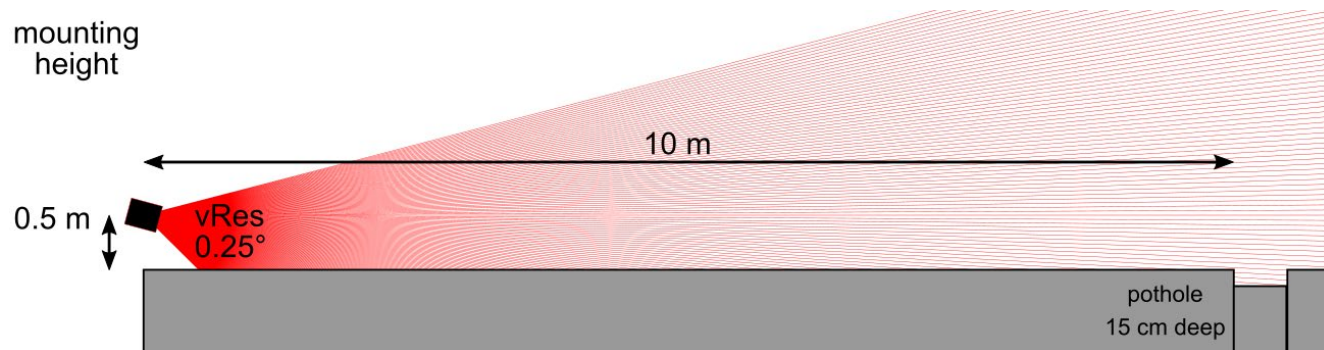


Example Use-Case Potholes – Mounting Height Matters

1.5 m
(rooftop,
behind windshield)

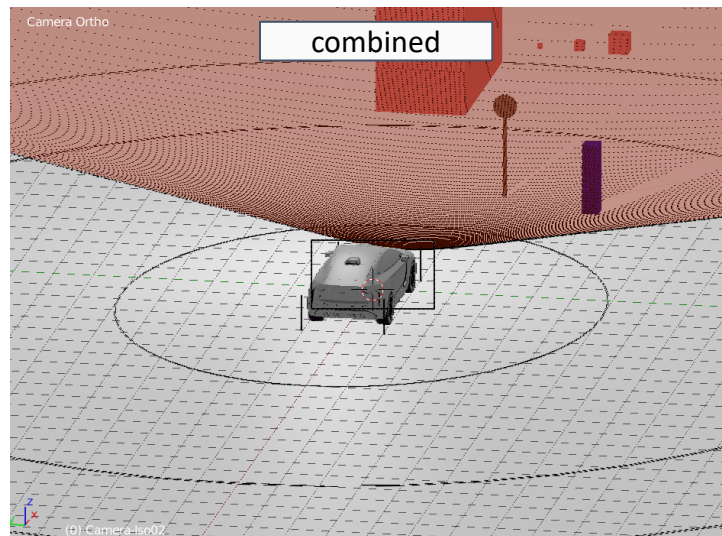
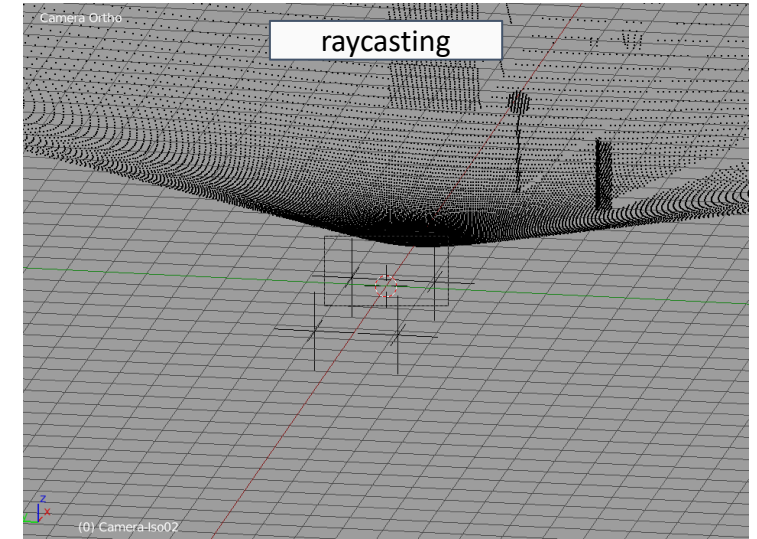
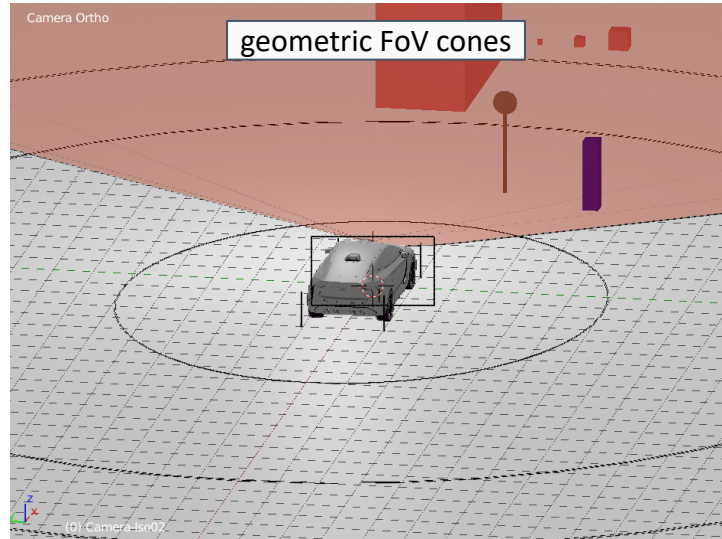
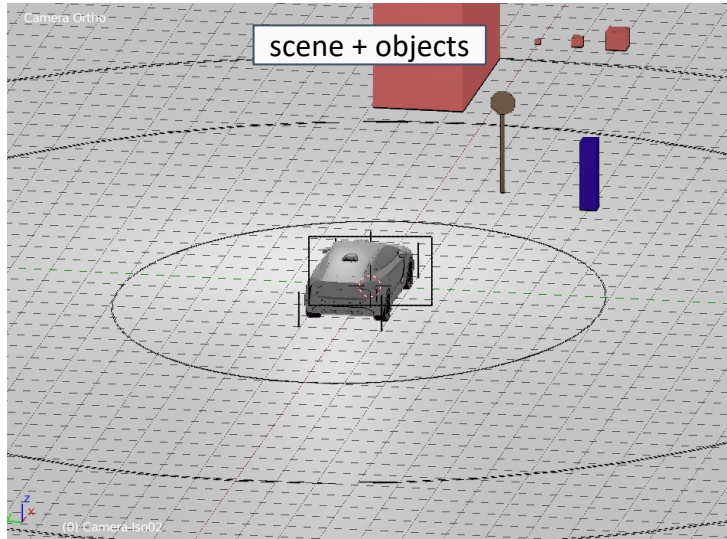


0.5 m
(front grille,
headlights)



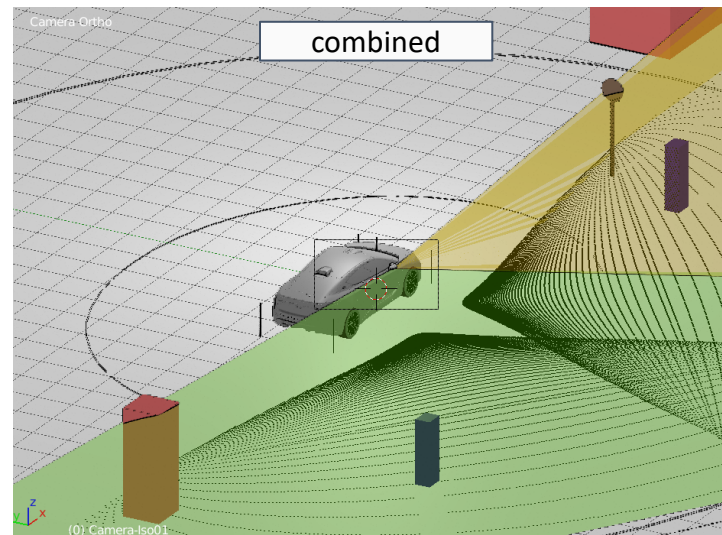
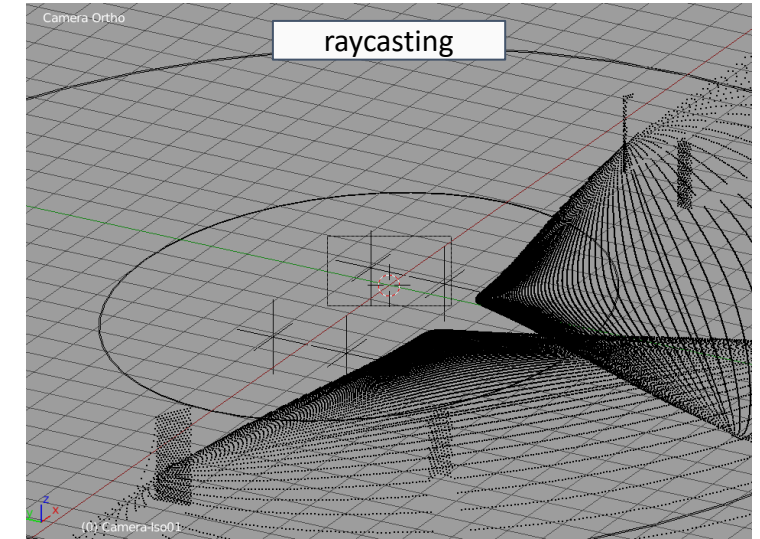
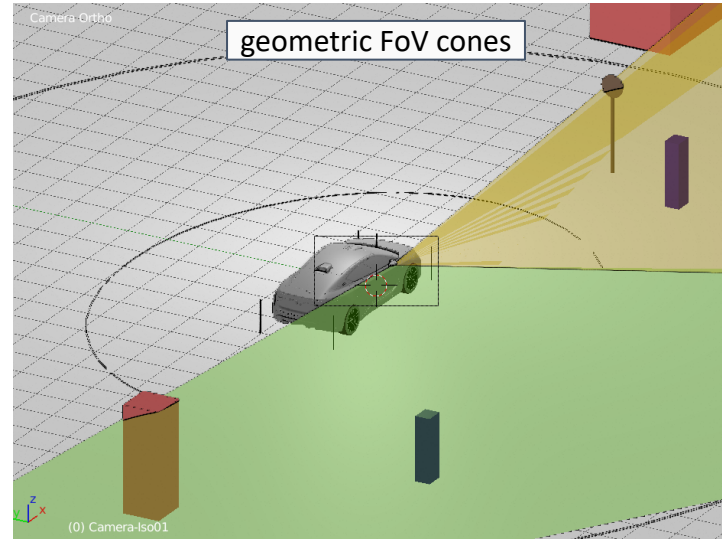
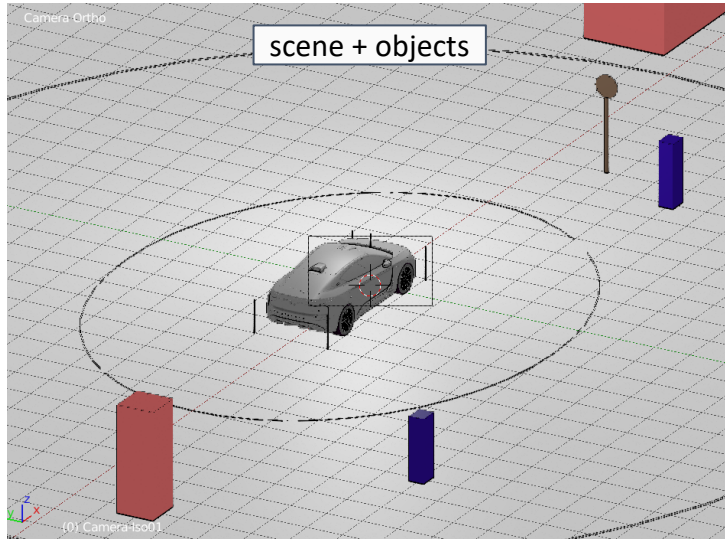
∕ Flat incidence angle challenging -> high mounting position preferred

From Geometric Coverage To Raycasting



/ Analysis of resolution requirements

From Geometric Coverage To Raycasting



- / Analysis of resolution requirements
- / Increased resolution for sensor combinations?

Summary of Part I



- Geometric FoV models are good for rapid analysis of coverage in various use cases
- Sensor placement is critical for detection of certain objects
- Raycasting allows for analysing resolution requirements
- For detection probabilities, range estimations, environmental effects, etc. -> a physical model is required!

Automotive Sensors

- Advanced driver assistance systems (ADAS) sensors and example applications



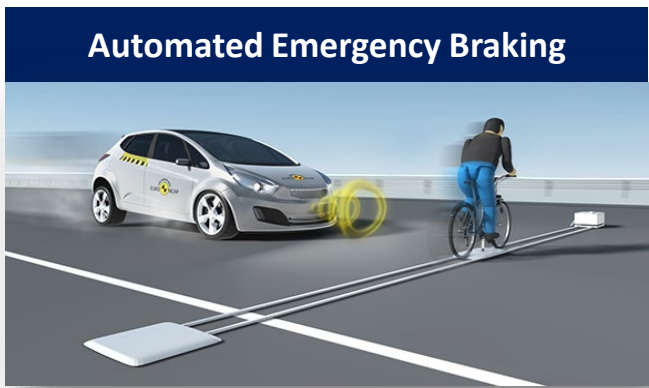
<https://www.bosch-mobility-solutions.com/>



<https://www.kostal-automobil-elektrik.com/>



<https://www.blickfeld.com/>



<https://www.openpr.com/>



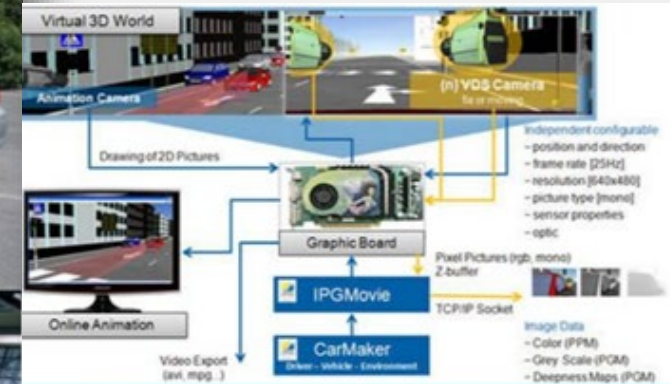
<https://www.bosch-mobility-solutions.com/>



<https://www.everythingrf.com/News/details>

Problem Statement

- Validation of these systems is done with real test drives which are expensive, time consuming, safety critical.
- ADAS Safety functions require a proof distance of about 240 million km*.
- Methods for ADAS Validation
 - Prototypes and road trials
 - Model-in-the-Loop Testing (driving simulator)
 - Hardware-in-the-Loop Testing (senor test benches)
 - **Combination of simulation & real world test: hybrid strategy.**
- **Required:** Development and validation of physical ADAS sensor models



Sources:

- MAGNA Steyr, IPG, Toyota, FTG
- *Handbook of Driver Assistance Systems, Editors: Winner, H., Hakuli, S., Lotz, F., Singer, C.

LiDAR FMU Model Block Diagram



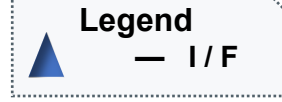
Co-simulation

Driving Simulation Platform

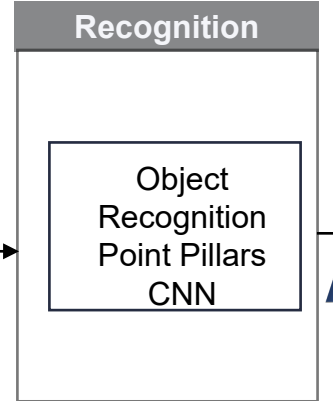
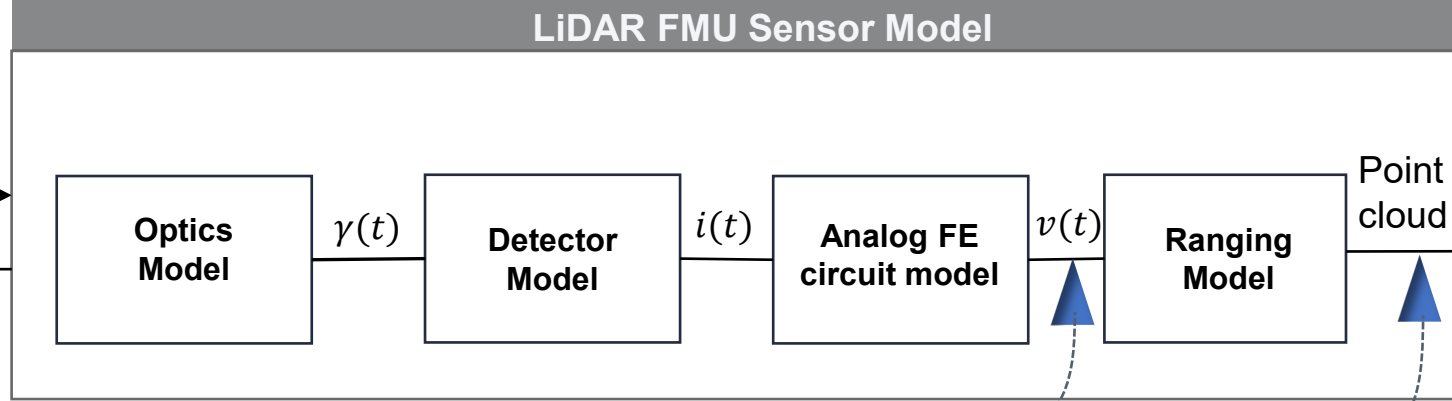
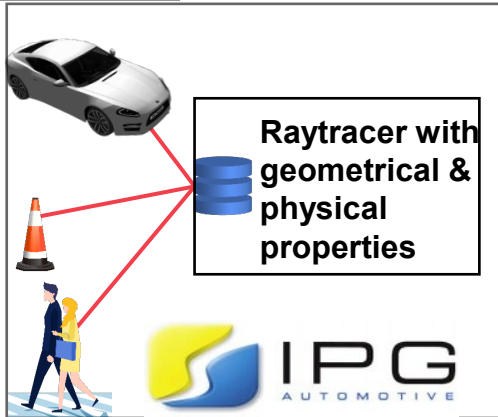
Environment

Spatial Drawing

osi3::LidarSensorView



Sensor Signal Flow



osi3::LidarSensorViewConfiguration

Spatial Input

Analog Circuit model output

Point Cloud Data

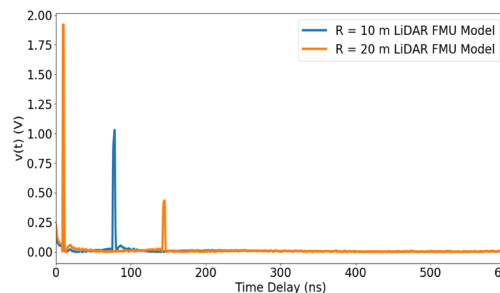
Object Recognition

I / F Output

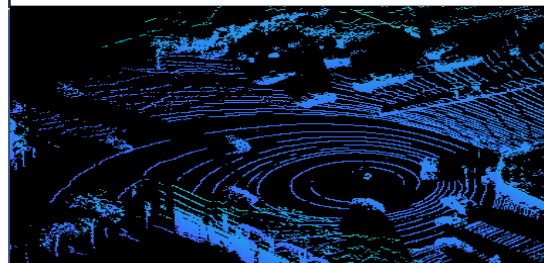
◆ Raytracing trace the path of light rays as they bounce back from the objects in the scene



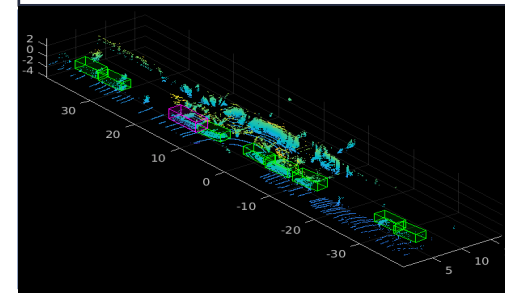
◆ The signal contains the information about the amplitude level and range of the objects.



◆ Distance to the object, horizontal/vertical angle of the ray and reflection intensity.



◆ Information such as the type, position, and size of the object.

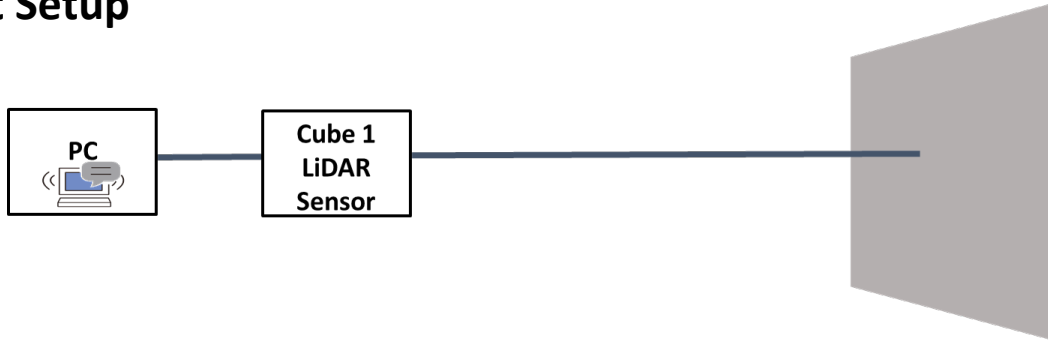


$\gamma(t)$ # of photons
 P_{opt} optical power
 $i(t)$ photo current
 $v(t)$ signal voltages

Source: MATLAB, Concept Source : SOKEN, INC

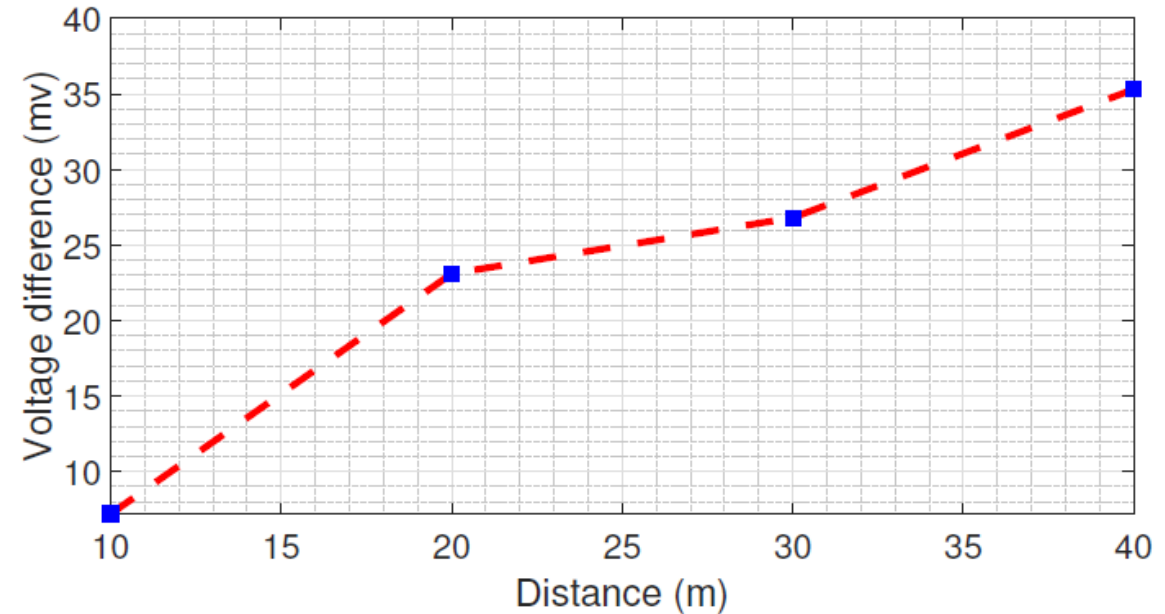
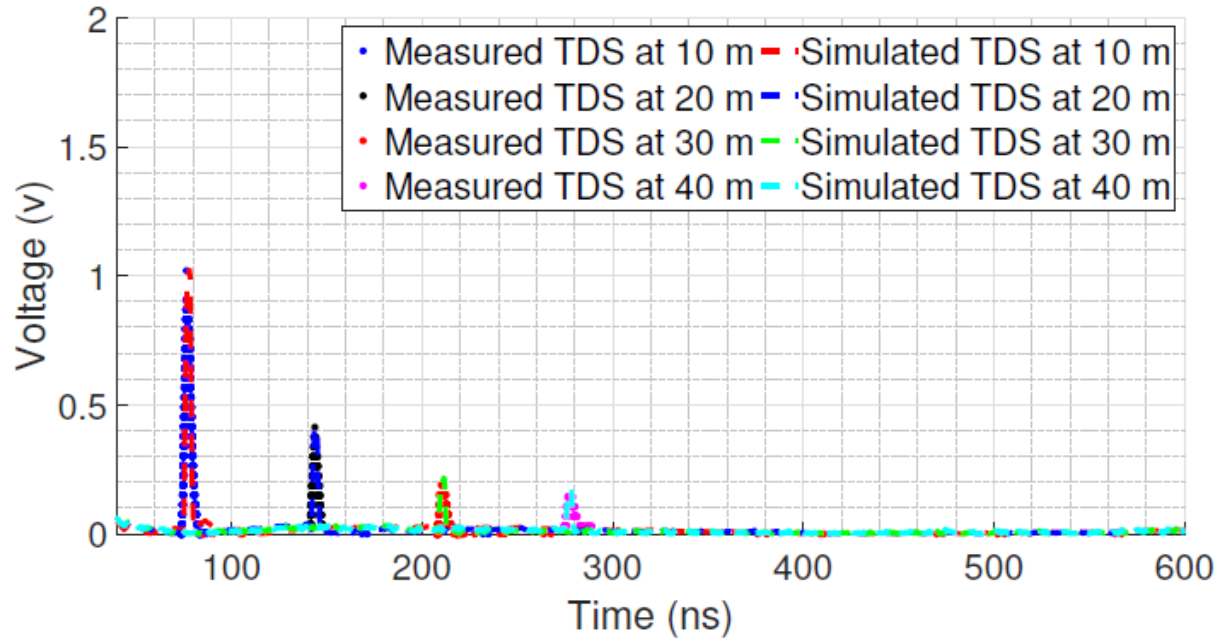
LiDAR FMU and Cube 1 Analog Circuit Model Output Comparison

Test Setup



10% reflective Lambert target

■ Cube 1/LiDAR FMU model amplitude, peak shape and ranges matched for Lambert target.



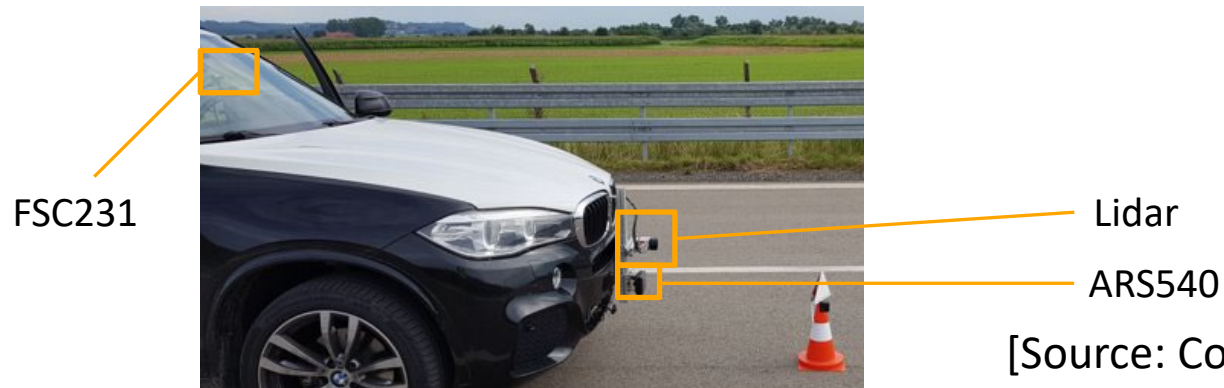
Proving Ground FAKT Motion in Benningen



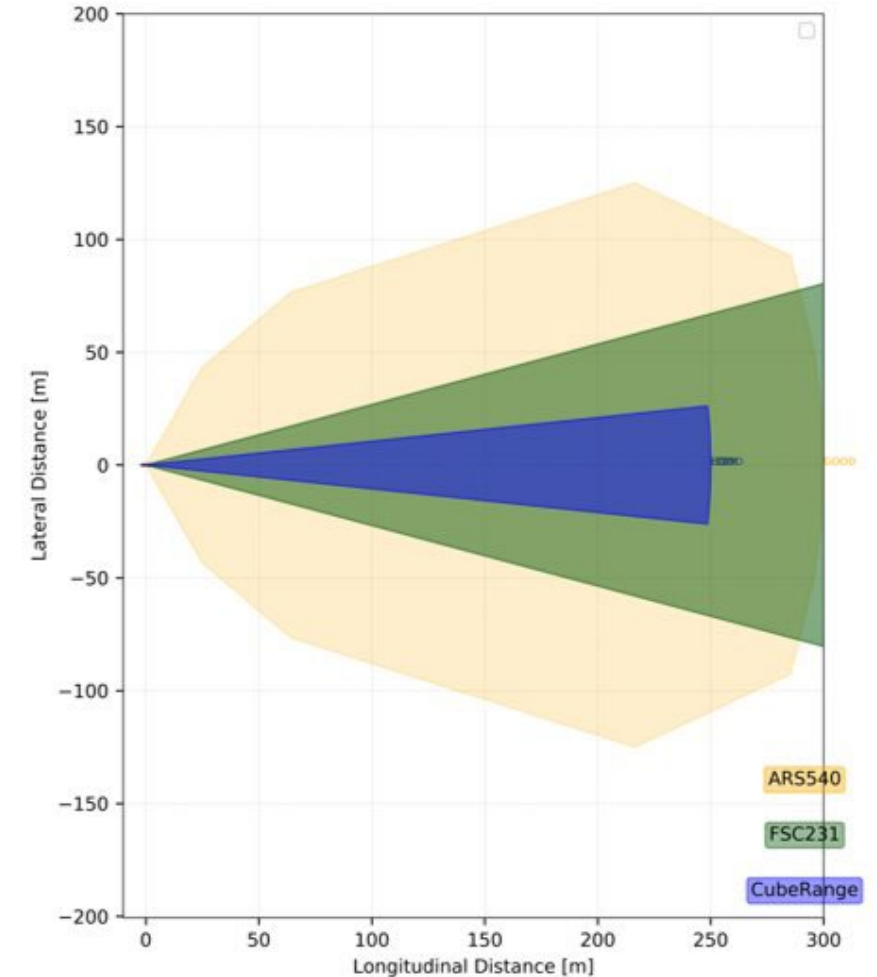
Sensors Used for EuroNCAP CPLA Scenario

Conti's BMW X5:

- ARS540 (300 m range, FOV: +/-60 deg azimuth and +/-20 deg)
- FSC231 (8.3 MP, FOV: +/-15 deg azimuth, elevation tbd)
- Blickfeld **LiDAR Cube Range 1** (250 m range, FOV: +/-9 deg azimuth, +/-6 deg elevation)
- Velodyne Ultra Puck (32 ch, FOV: 360 deg, -25/15 deg in elevation) mounted on the roof (Ultra Puck used as a reference sensor)
- PwrPK7 DGPS

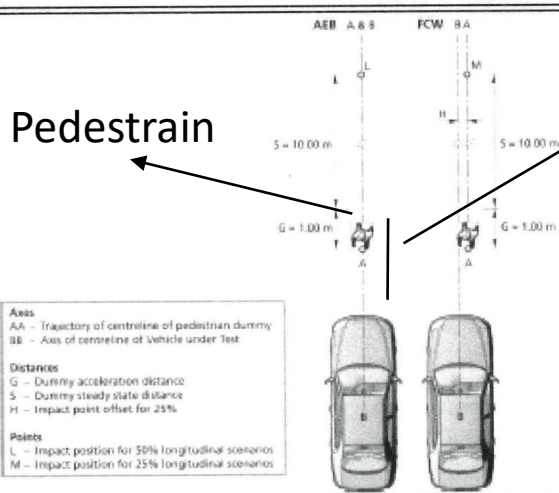


[Source: Continental]



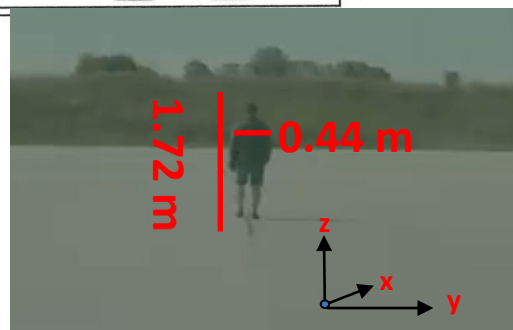
CPLA Scenario and LiDAR Sensor Specification

Name	Car-to-Pedestrian Longitudinal Adult (CPLA)		
Function	Collision avoidance		
Road type	Straight road	Target object	Pedestrian
Maneuver	Lane following	Target movement	Longitudinal
Description	Pedestrian on the same lane, moving in longitudinal direction		

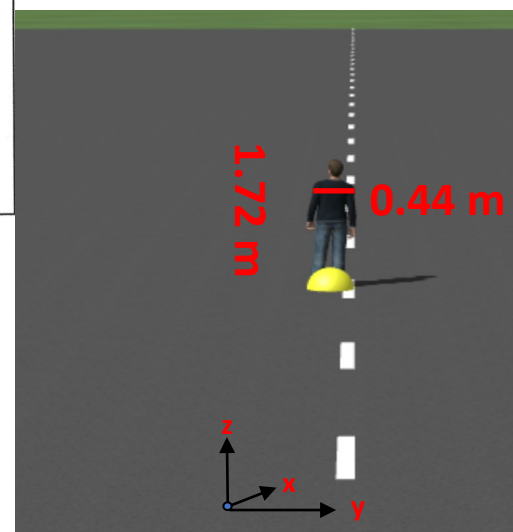


Starting point: 30 m from pedestrian for ego vehicle

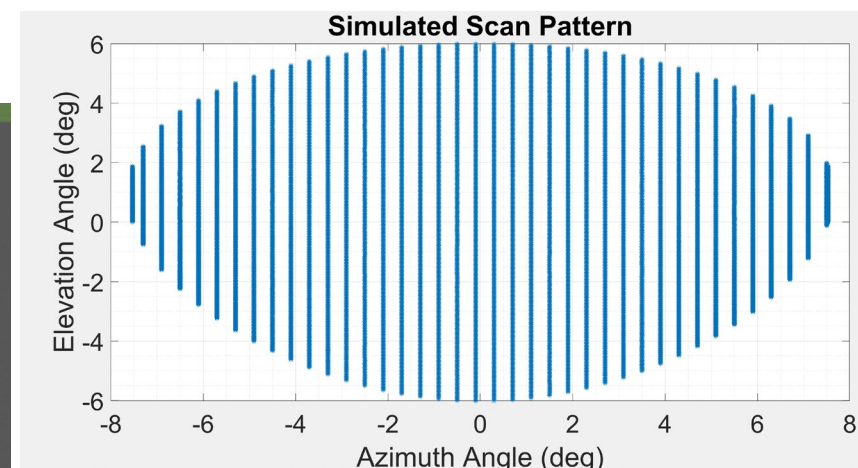
Ego was moving 10 km/h and pedestrian was moving 5 km/h



Real Scene



Simulation Scene IPG CarMaker 9.0.1



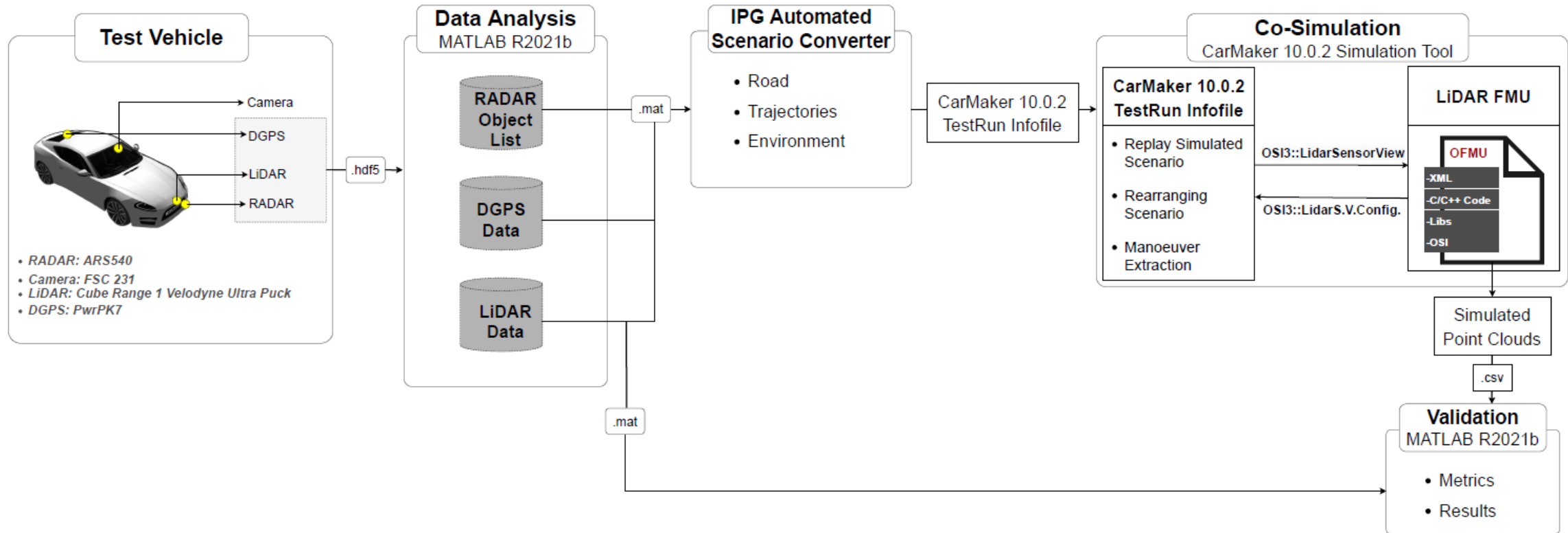
FOV (18° Horizontal and 12° Vertical), 400 scan lines and 0.4° angle spacing, max. detection range 250 m, min. detection range 5 m

Proving Ground (Real Environment) Measurement and... ...@Virtual Environment Results



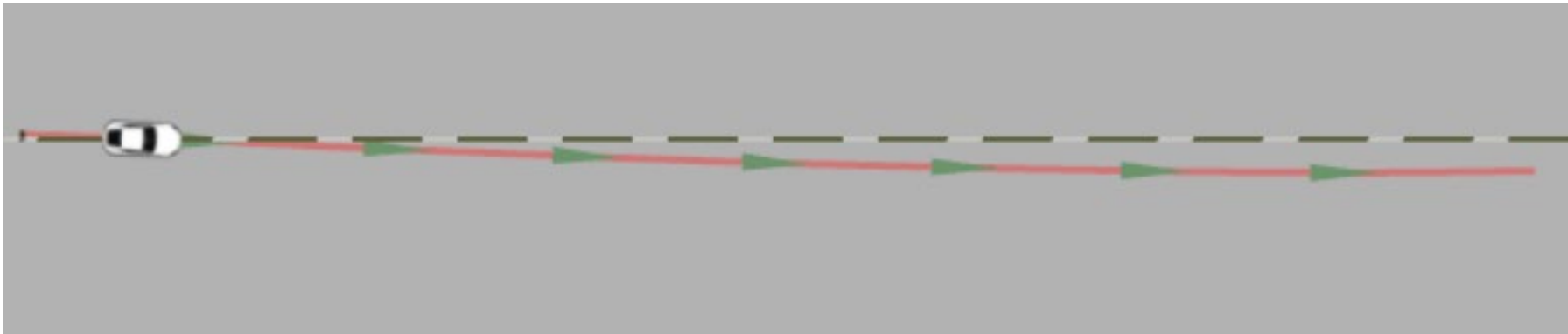
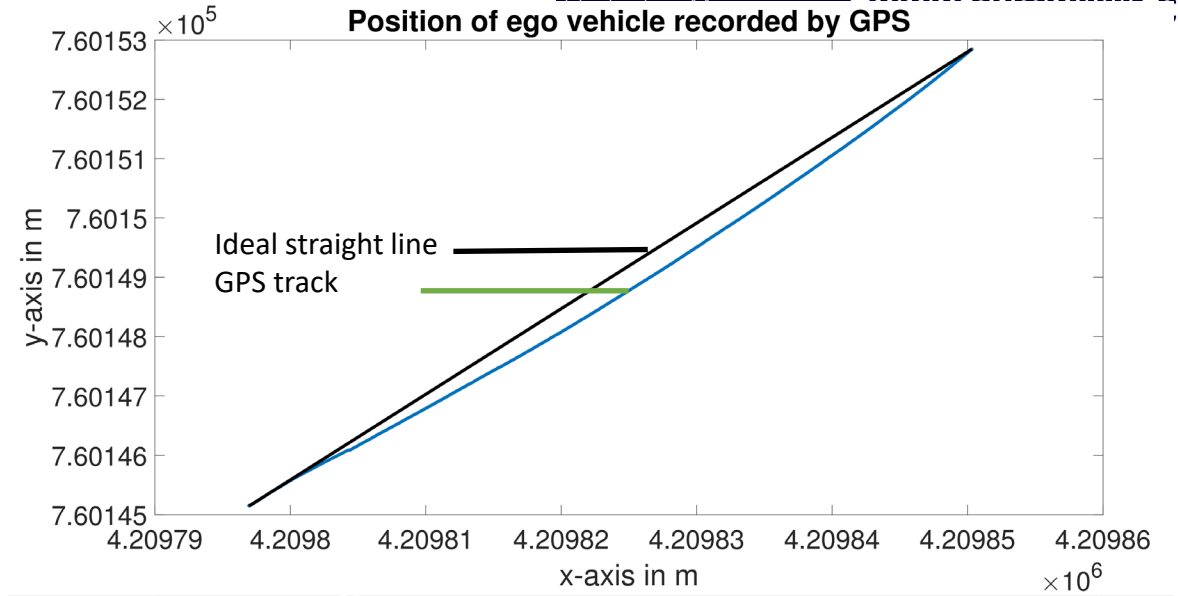
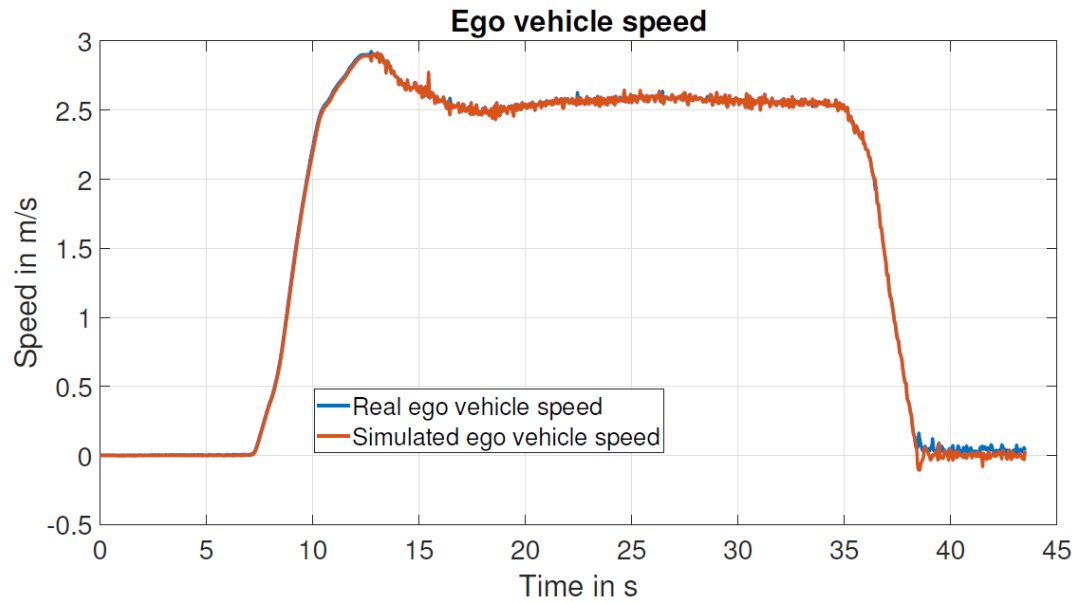
- Euro NCAP CPLA scenario/
test
- LiDAR FMU point clouds
are ideal and only
consider noise not any
other impairment yet.

Tool Chain for LiDAR FMU Model Validation



- For validation, **Cube Range 1 and LiDAR FMU** model point cloud data for CPLA scenario compared frame by frame and evaluated by different metrics
- No validation (yet) on object detection level

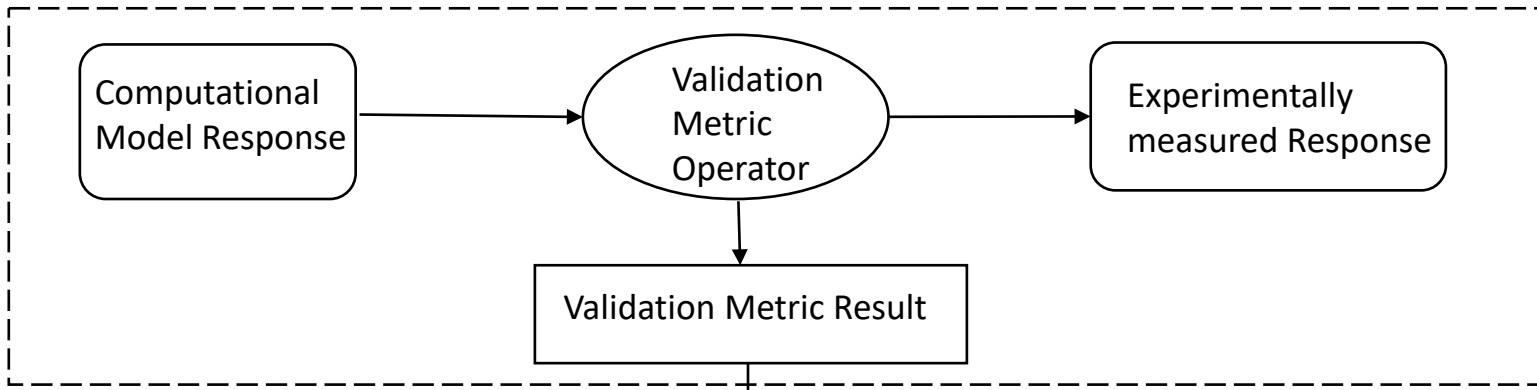
Ego Vehicle Speed Profile & Trajectory in IPG CarMaker



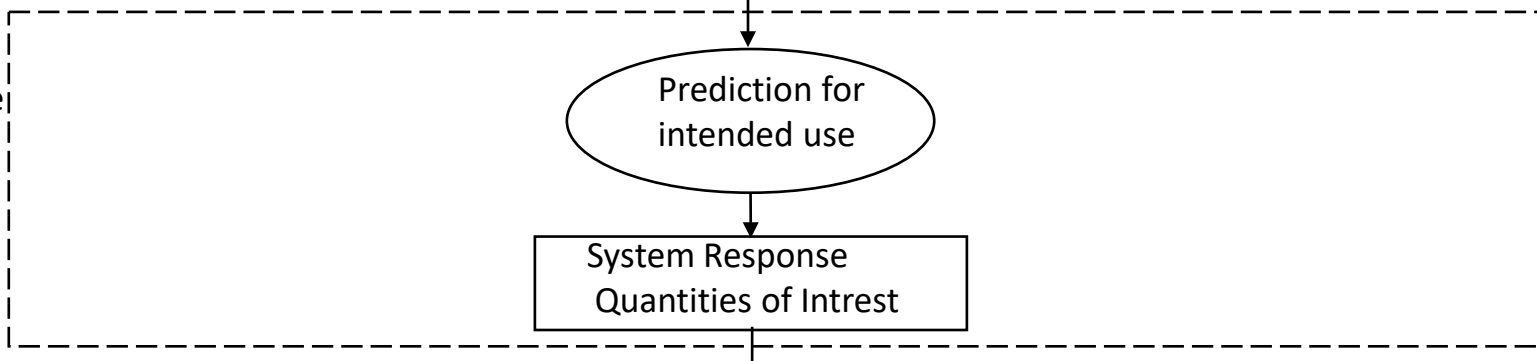
- Ego car position in x-y plane, geodetic to ECEF coordinates
- Earth-centered, Earth-fixed coordinate system (acronym ECEF)

A Generic Validation Method Vehicle Environment Sensor Models

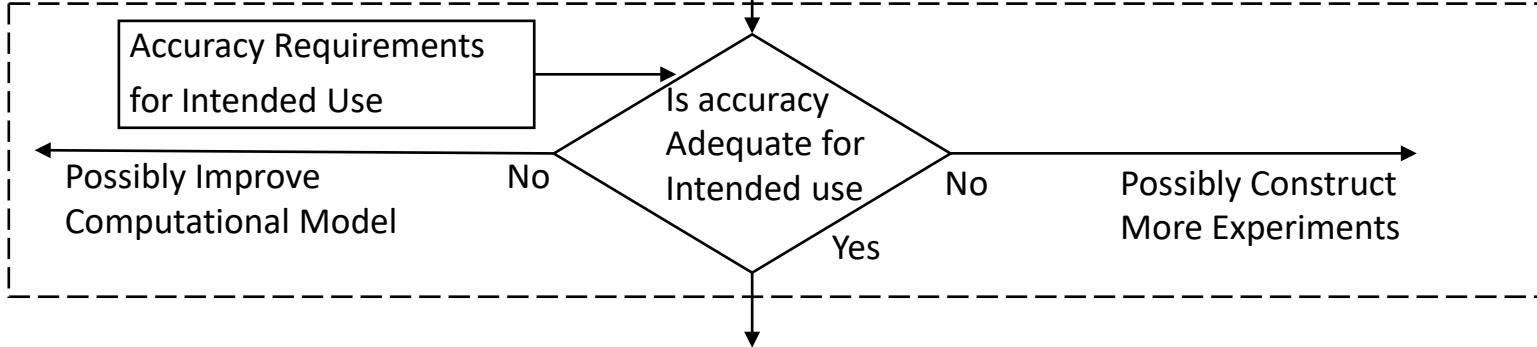
1. Assessment of Model Accuracy by Comparison with Experimental Data



2. Interpolation or Extrapolation of the Model to the Intended Use



3. Decision of Model Adequacy for Intended Use



Note: So far only assessment of model accuracy

A. Schaermann. et.al, "Validation of vehicle environment sensor models," 2017 IEEE Intelligent Vehicles Symposium (IV), 2017, pp. 405-411, doi: 10.1109/IVS.2017.7995752.

LiDAR Sensor Model Validation

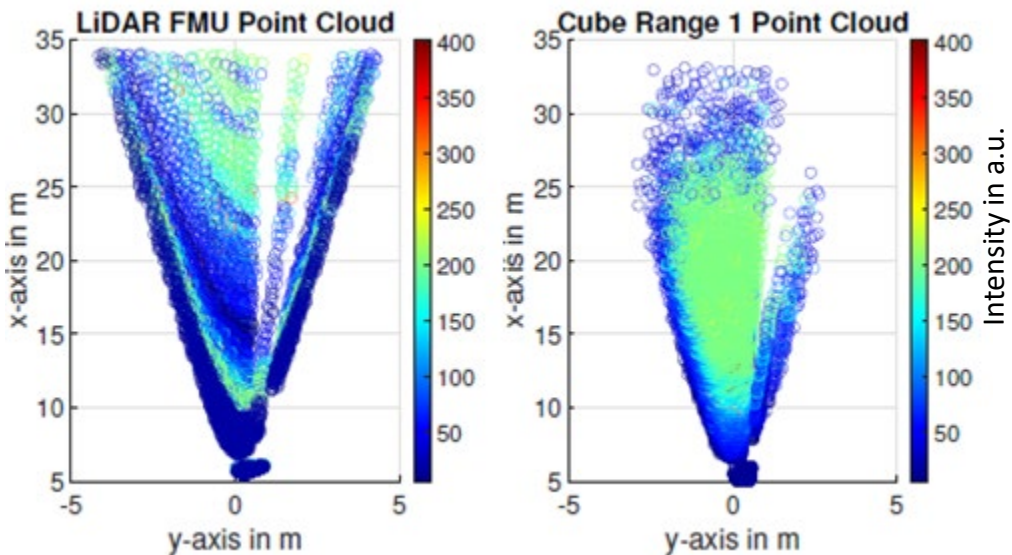
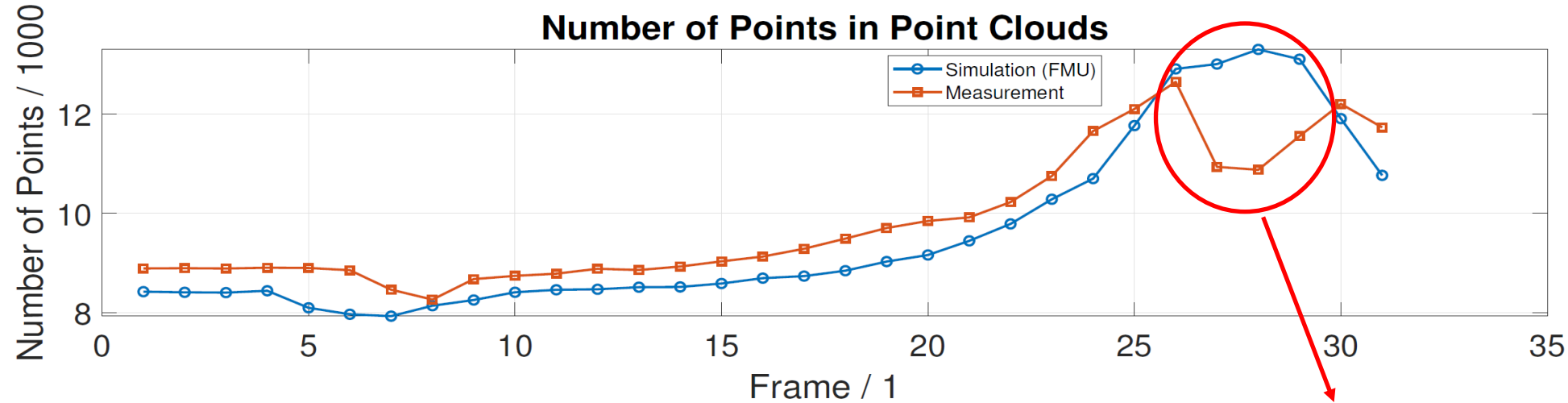


■ Assessment of model accuracy at point cloud level

- LiDAR FMU and Cube Range 1-point clouds and occupancy grid maps (OGs) are compared frame by frame using appropriate metrics.
- The model is accurate if
 - Correlation/similarity is above 65% when validation metric is applied to distance distribution, and OGs generated from x, y coordinates of distance
 - Correlation/similarity is above 40% when validation metric is applied to OGs generated from x, y, z coordinates of distance and also consider the corresponding intensity values

Note: The correlation/similarity does not depend only on the fidelity of the sensor model but also on environmental modeling.

LiDAR FMU and Cube Range 1 Number of Point Clouds Comparison... ...@Frame by Frame



Orientation of the object in simulation and real measurement is different for 27th, 28th and 29th frame

Metrics Studies on Distance Distribution of Point Cloud Level



- Pearson's linear correlation coefficient¹
- Kendall rank correlation coefficient²
- Spearman's rho³
- Barons cross correlation coefficient⁴

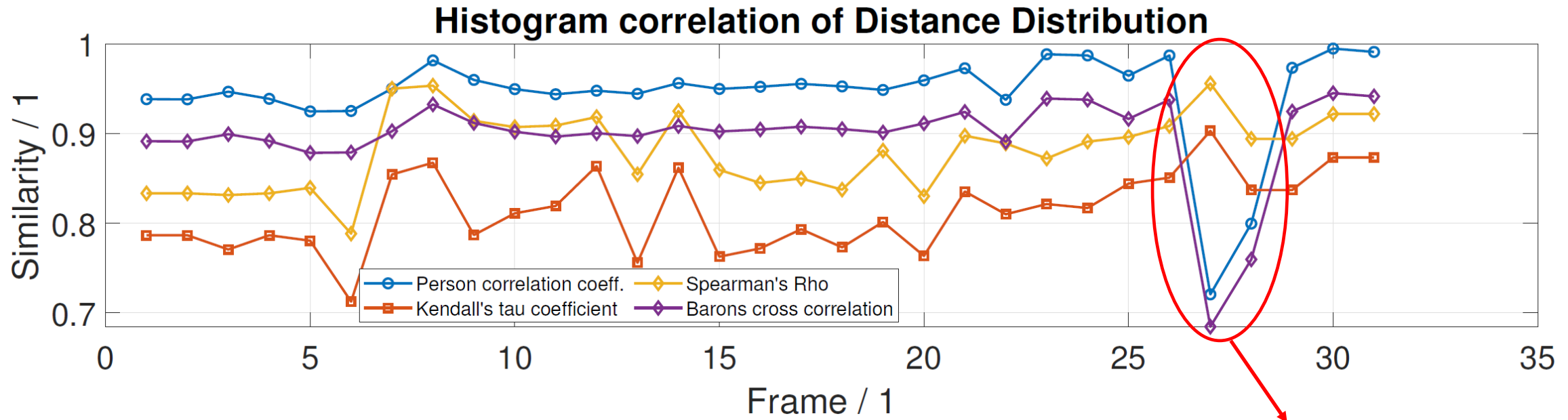
¹Gibbons, J.D. Nonparametric Statistical Inference. 2nd ed. M. Dekker, 1985.

²Hollander, M., and D.A. Wolfe. Nonparametric Statistical Methods. Wiley, 1973.

³Kendall, M.G. Rank Correlation Methods. Griffin, 1970.

⁴T. Hanke et al., "Generation and validation of virtual point cloud data for automated driving systems.," 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC) 2017, pp. 1-6, doi: 10.1109/ITSC.2017.8317864.

Metrics Results Applied on Distance Distribution of Point Cloud Level



Orientation of the object in simulation and real measurement is different for 27th, 28th and 29th frame

- Pearson and Baron's correlations are better metrics as compared to others because they are more sensitive to environmental modelling.

Metrics Applied on 2-D Occupancy Grid Map

- Pearson's linear correlation coefficient¹
 - Kendall rank correlation coefficient²
 - Spearman's rho³
 - Barons cross correlation coefficient⁴
 - Occupied and free cell ratio metric⁵
 - Grid cell pulse response (GCPR)
- All the metrics mentioned above does not consider the intensity values of measured points.
- In this work, we have developed a grid cell pulse response (GCPR) metric that considers the distance and intensity values to validate the performance of LiDAR sensor model.

Note: 2-D occupancy grid map is generated from x and y coordinates of distance

¹Gibbons, J.D. Nonparametric Statistical Inference. 2nd ed. M. Dekker, 1985.

²Hollander, M., and D.A. Wolfe. Nonparametric Statistical Methods. Wiley, 1973.

³Kendall, M.G. Rank Correlation Methods. Griffin, 1970.

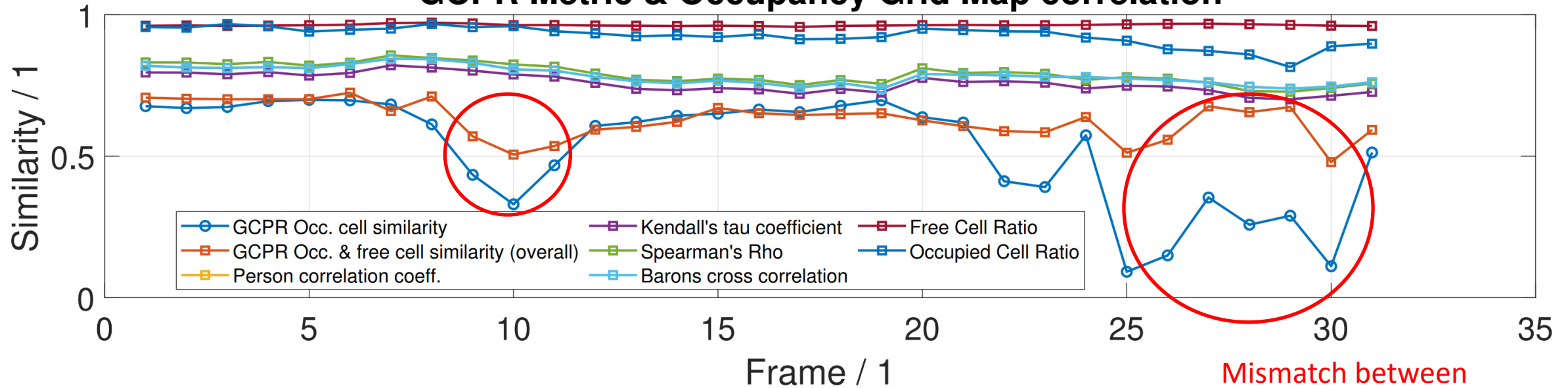
⁴T. Hanke et al., "Generation and validation of virtual point cloud data for automated driving systems.," 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC) 2017, pp. 1-6, doi: 10.1109/ITSC.2017.8317864.

⁵R. Grewe, et al., Evaluation method and results for the accuracy of an automotive occupancy grid.," 2012 IEEE International Conference on Vehicular Electronics and Safety (ICVES 2012), 2012, pp. 19-24, doi: 10.1109/ICVES.2012.6294297.

Result of the Metrics Applied on the 2-D Occupancy Grid... ...@Map



G CPR Metric & Occupancy Grid Map correlation



Mismatch between the intensity of simulated and measured point cloud

- Metrics such as Free cell ratio, Occupied cell ratio, Kendall's, Spearman, Barons, and Pearson's do not consider the intensity of point clouds and can't provide information about the modeled reflectivity of objects in a virtual environment.
- The correlation drops rapidly for the G CPR metric because it considers the distance and intensity values.

Conclusion



- LiDAR sensor model performance highly depends on environmental modeling.
- Currently, state-of-the-art metrics used to validate the fidelity of the LiDAR sensor model and do not consider the intensity of point clouds.
- That's why they can't validate the modeling of material properties in a virtual environment, and we need a metrics that can provide the correlation depending on the distance and intensity of point clouds.
- It is challenging to model the pedestrian's exact body posture and movement in the virtual scenario constructed by the sensors data.

Outlook



Next Milestones:

- Analysis of LiDAR measurement data obtained at the CARRISMA rain facility

Parameters to Be Investigated for LiDAR Sensor

- Influence on the reflectivity type, values (ρ in %) and changes in the optical properties of the target due to the wetness of the target surface.
- Impact of water-particles on the SNR (SNR *in dB*) of LiDAR sensor.
- Received Power (P_r *in dB*) .
- Water-particles clutter (σ_{rb} in dBm^2/m^3) detection by the LiDAR sensor (false alarm due to backscattering at water-particles).

Outlook



Rain Rate (mm/h) at Carissma	Precipitation Type
16	Medium
32	Heavy
66	Very heavy
82	Very heavy
98	Very heavy

Fog Type	Fog Visibility (m) at Carissma (tbd)
Fog Light	350
Fog Thick	100
Fog Dense	50
Very Dense	25
Extreme Dense	10

Source:
 Meteorological Office UK. (2020). Homepage of the Meteorological Office - How we measure visibility. Retrieved January 25, 2020, from <http://www.metoffice.gov.uk/guide/weather/observations-guide/how-we-measure-visibility>

Shepard, F. D. (1996). Reduced visibility due to fog on the highway. Transportation Research Board, National Research Council (Ed.). National Academy Press. Washington, D.C., USA. ISBN 0-309-06006-0.

Outlook (CARISSMA Indoor Test Facility)

No rain

Medium rain (16 mm/h)

Heavy rain (32 mm/h)

Dense fog (50 m)



■ Rain hall area is 50 m × 4 m and consist of 12 segments and each have 4.2 m length

■ Fog hall has 50 m × 6 m area

