Hochschule Kempten University of Applied Sciences

Blickfeld LiDAR / scan your world

Development and Validation of Automotive LiDAR sensor Model with standardized interfaces

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Overview

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

UAS Kempten: Objectives in VIVALDI

- **Development** of physical LiDAR/RADAR sensor behavioral models using standardized interfaces
  - Open Simulation Interface (OSI)
    - OSI is a generic interface that uses a protocol buffer message format developed by Google to exchange information between the environmental simulation tools, sensor models, and ADAS systems
  - Functional Mockup Interface (FMI)
    - FMI is generic interface it allows the accessible exchange of simulation models between different tools
    - A component which implements the interface is called a Functional Mockup Unit (FMU)
- **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 on the point cloud level

ASAM e.V. Open Simulation Interface (OSI): https://opensimulationinterface.github.io/open-simulation-interface/index.html
FMI Source: https://fmi-standard.org/

Automotive Sensors

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

Adaptive Cruise Control

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

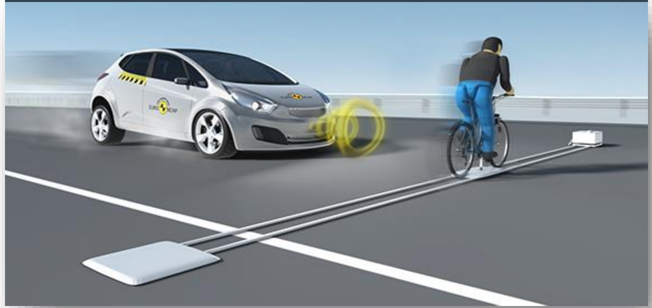
Camera

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

LiDAR

https://www.blickfeld.com/

Automated Emergency Braking



https://www.openpr.com/

Ultrasonic Sensors

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

RADAR

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

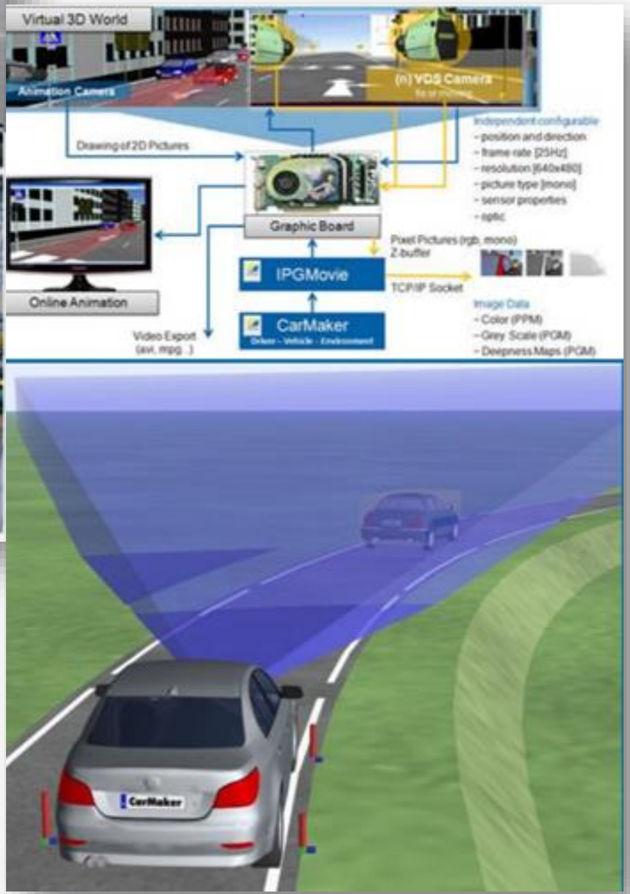
Problem Statement

- 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*

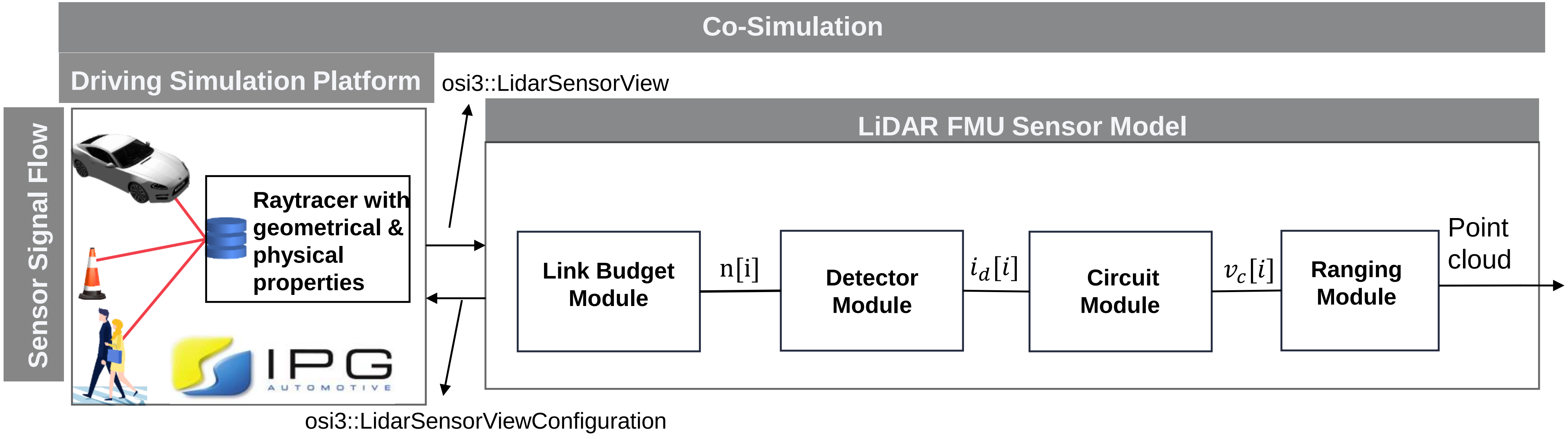
- Methods for ADAS Validation
  - Prototypes and road trials
  - Model-in-the-Loop Testing (driving simulator)
  - Hardware-in-the-Loop Testing (senor test benches)
  - **Combination of simulation & real-world test: hybrid strategy**

- **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

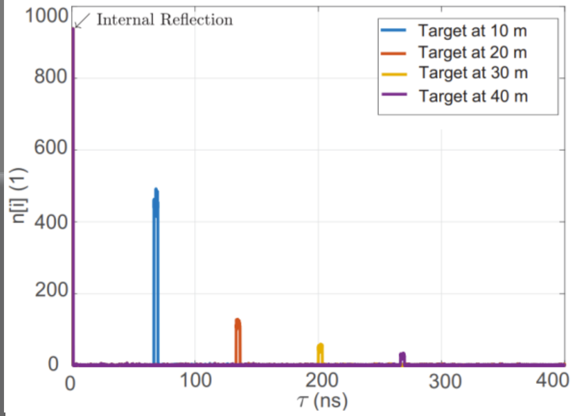


$n[i]$ # of photons
$i_d(t)$ photo current
$v_c(t)$ signal voltages

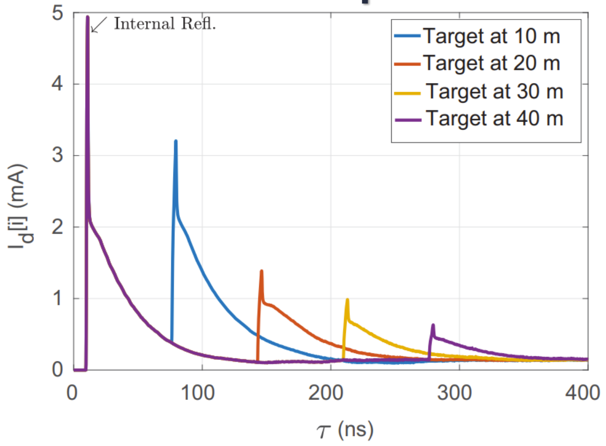
The exemplary output is for the 5% reflective Lambertian plate

Example Output

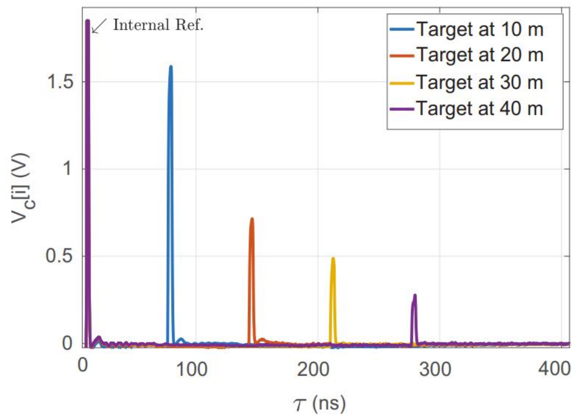
Link Budget Module output



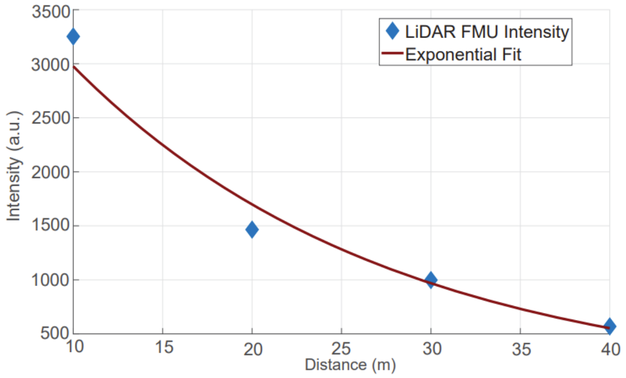
Detector Module output



Circuit Module output



Ranging Module output



Model Development And Validation Process Overview

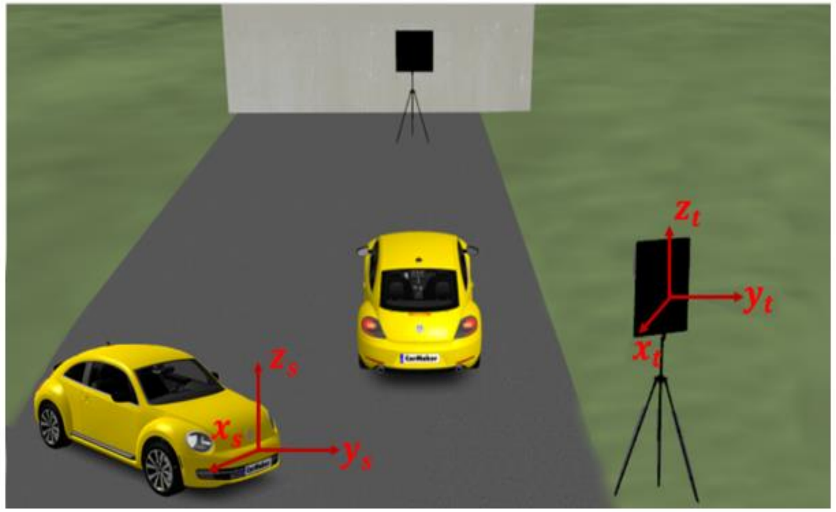
Model development and validation

Steps	Step 0 Basic principle validation	Step 1 Basic validation	Step 2 Recognition error validation	Step 3 Extended validation
				
Implementation contents	Basic validation in the Lab tests	Validation under normal condition	Validation under sensing weakness condition	Validation under real traffic environment
	Verification of sensor model working	Verification of sensor model at the proving ground	Implementation of space design model containing sensing weakness	Extension of environment model

- In this presentation, we will show the results of validation step 0 and step 1

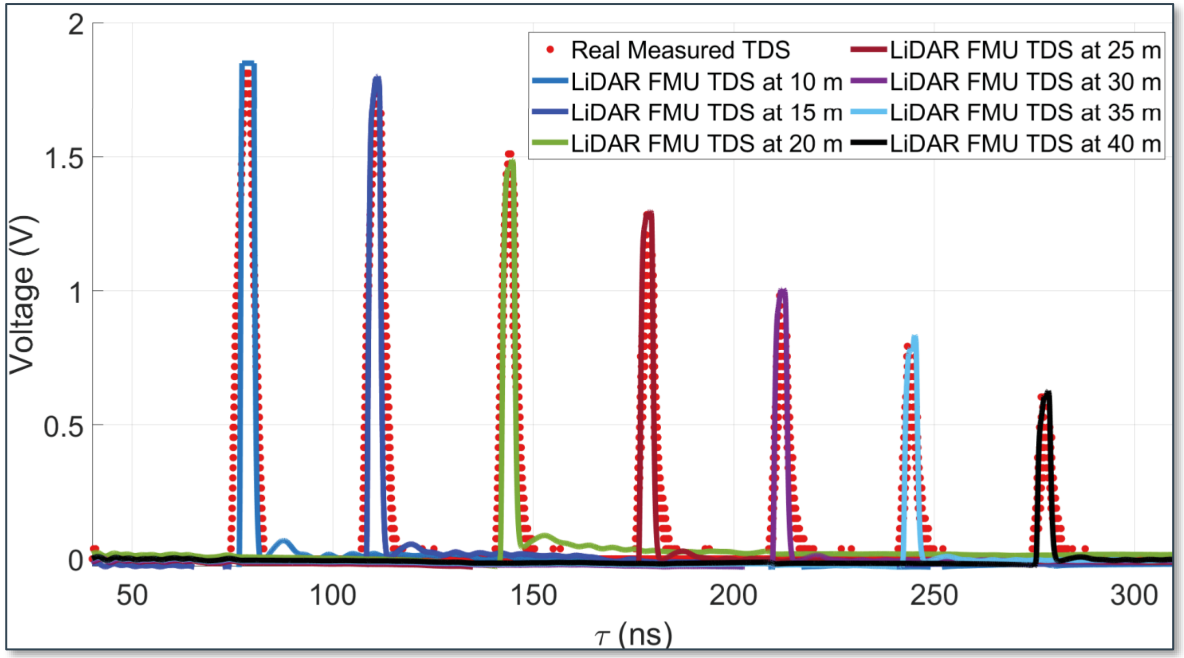
Basic Principle Validation (Lab Tests)

LiDAR FMU and Cube 1 analog circuit model output comparison for 10% reflective Lambertian target



Static simulation scene

Real setup



- Cube 1/LiDAR FMU model amplitude, peak shape and ranges matched for Lambert target
- To quantify the amplitude difference Δv, we use the Mean Absolute Percentage Error (MAPE) metric

$$\text{MAPE} = \frac{1}{n}\sum\left|\frac{y_i - x_i}{y_i}\right| * 100$$

- Where y_i is the simulated value, the measured value is denoted by x_i , and n shows the total number of data points
  The MAPE of voltages is 1.7%

Haider, A.; Pigniczki, M.; Köhler, M. H.; Fink, M.; Schardt, M.; Cichy, Y.; Haas, L.; Zeh, T.; Poguntke, T.; Jakobi, M.; Koch, A.W. Development of High-Fidelity Automotive LiDAR Sensor Model with Standardized Interfaces. Under review in Sensors 2022

Swamidass, P. Mean absolute percentage error (MAPE), Proc. Encyclopedia Prod. Manuf. Manage., 2000, pp. 30.

Basic Principle Validation (Lab Tests)

LiDAR FMU and Cube 1 validation on the point cloud level

Three KPIs based on expert knowledge to validate the sensor model on the point cloud

- The number of received points N_{points} from the surface of the simulated and real objects of interest
- The comparison between the mean intensity I_{mean} values of received reflections from the surface of the simulated and real targets
- The distance error d_{error} of point clouds obtained from the actual and virtual objects should not be more than the range accuracy of the real sensor, that is 2 cm in this case

Haider, A.; Pigniczki, M.; Köhler, M. H.; Fink, M.; Schardt, M.; Cichy, Y.; Haas, L.; Zeh, T.; Poguntke, T.; Jakobi, M.; Koch, A.W. Development of High-Fidelity Automotive LiDAR Sensor Model with Standardized Interfaces. Under review in Sensors 2022

Expected Results (Lab Tests)

LiDAR FMU and Cube 1 validation on the point cloud level

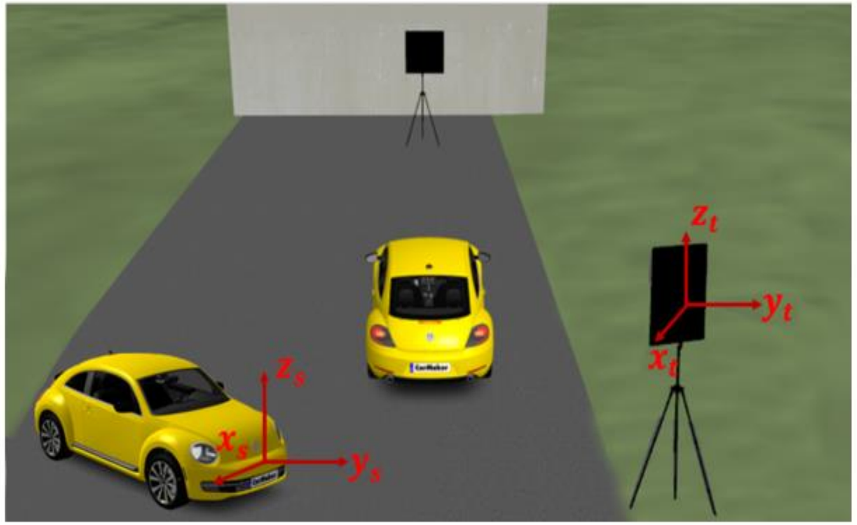
- The presented LiDAR sensor model includes accurate modeling of the scan pattern and a complete signal processing toolchain of a LiDAR sensor

- Furthermore, the simulated object's material properties, dimension, and orientation are the same as real objects

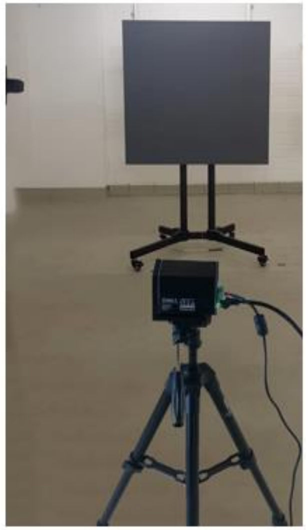
- It is expected that simulation results should be close to real

Test setup for Lab Tests and Virtual Environment

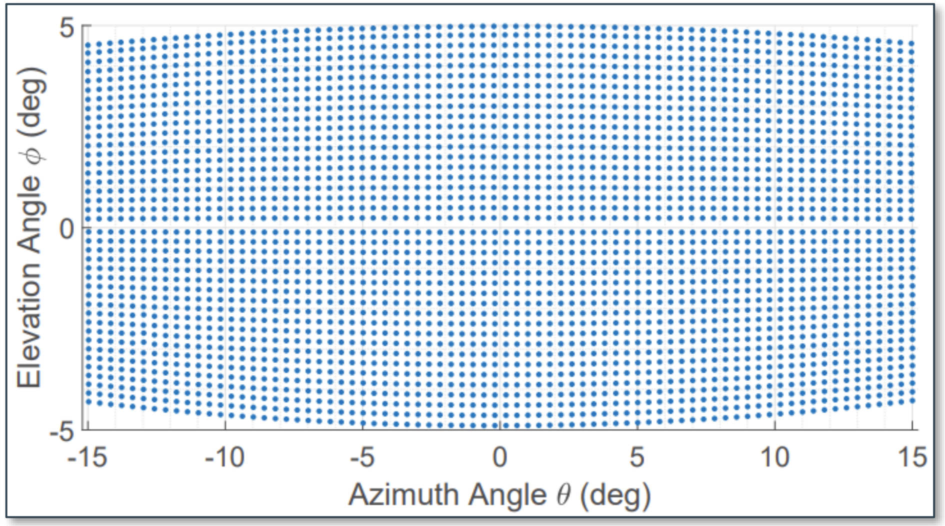
- 10% Lambertian plate were placed infront of the ego vehicle and measurement was taken at the relative distance of 5m, 10 m, 15 m, 20 m, 25 m, 30 m, 35 m, and 40 m.



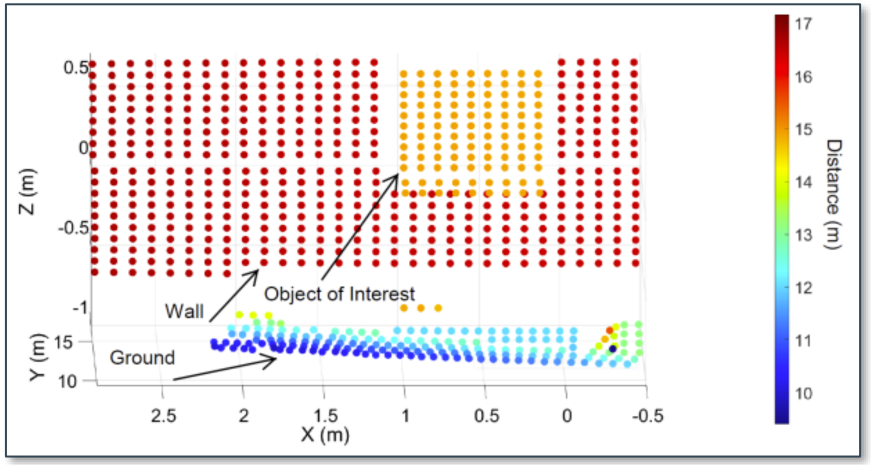
Static simulation scene



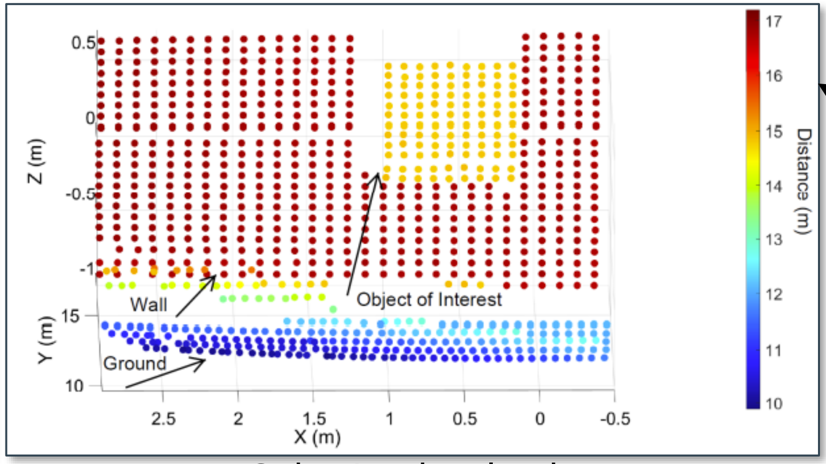
Real scene



FOV (30° Horizontal and 10° Vertical), 80 scan lines and 0.4° angle spacing, max. detection range 250 m, min. detection range 5 m



LiDAR FMU point clouds



Cube 1 point clouds

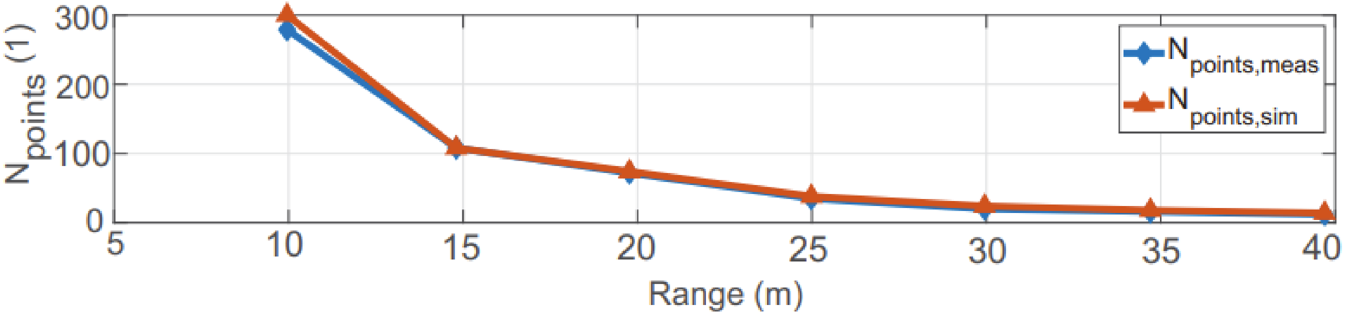
Exemplary visualization of the Cartesian point clouds received from all the objects in the FoV of LiDAR FMU and real sensor

Haider, A.; Pigniczki, M.; Köhler, M. H.; Fink, M.; Schardt, M.; Cichy, Y.; Haas, L.; Zeh, T.; Poguntke, T.; Jakobi, M.; Koch, A.W. Development of High-Fidelity Automotive LiDAR Sensor Model with Standardized Interfaces. Under review in Sensors 2022

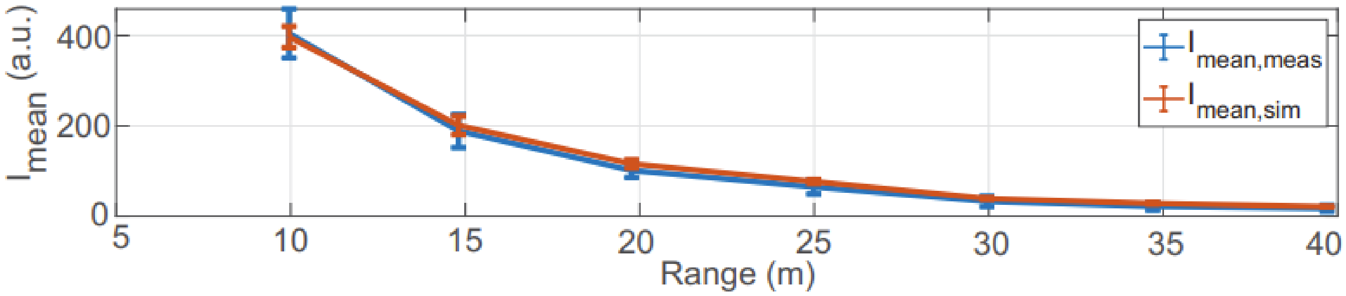
Basic Principle Validation (Lab Tests)

LiDAR FMU and Cube 1 validation on the point clouds level

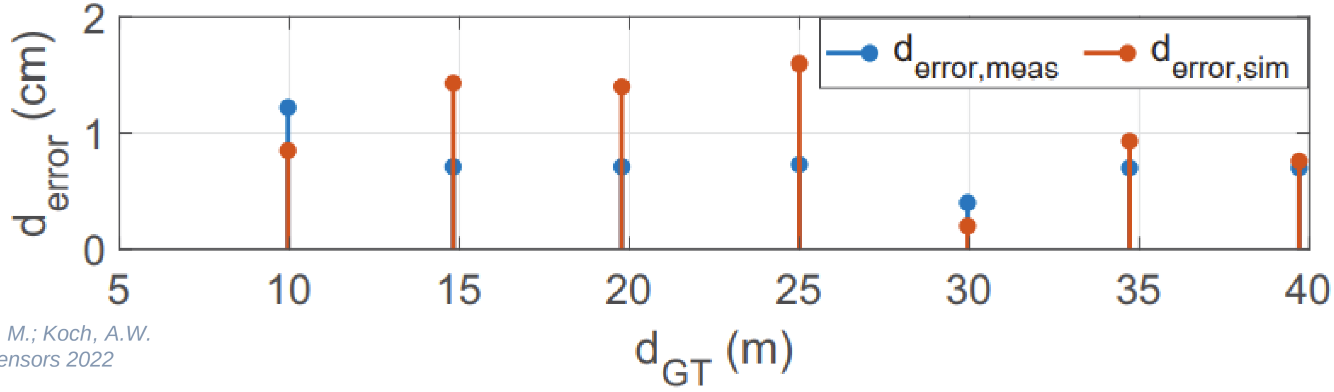
- The MAPE for the N_{points} is 8.5%
- The MAPE for the I_{mean} is 9.3%
- The distance error d_{error} is calculated as $d_{error} = d_{GT} - d_{mean/sim}$
- The d_{GT} distance is calculated from the sensor reference point to the center of the target



(a)

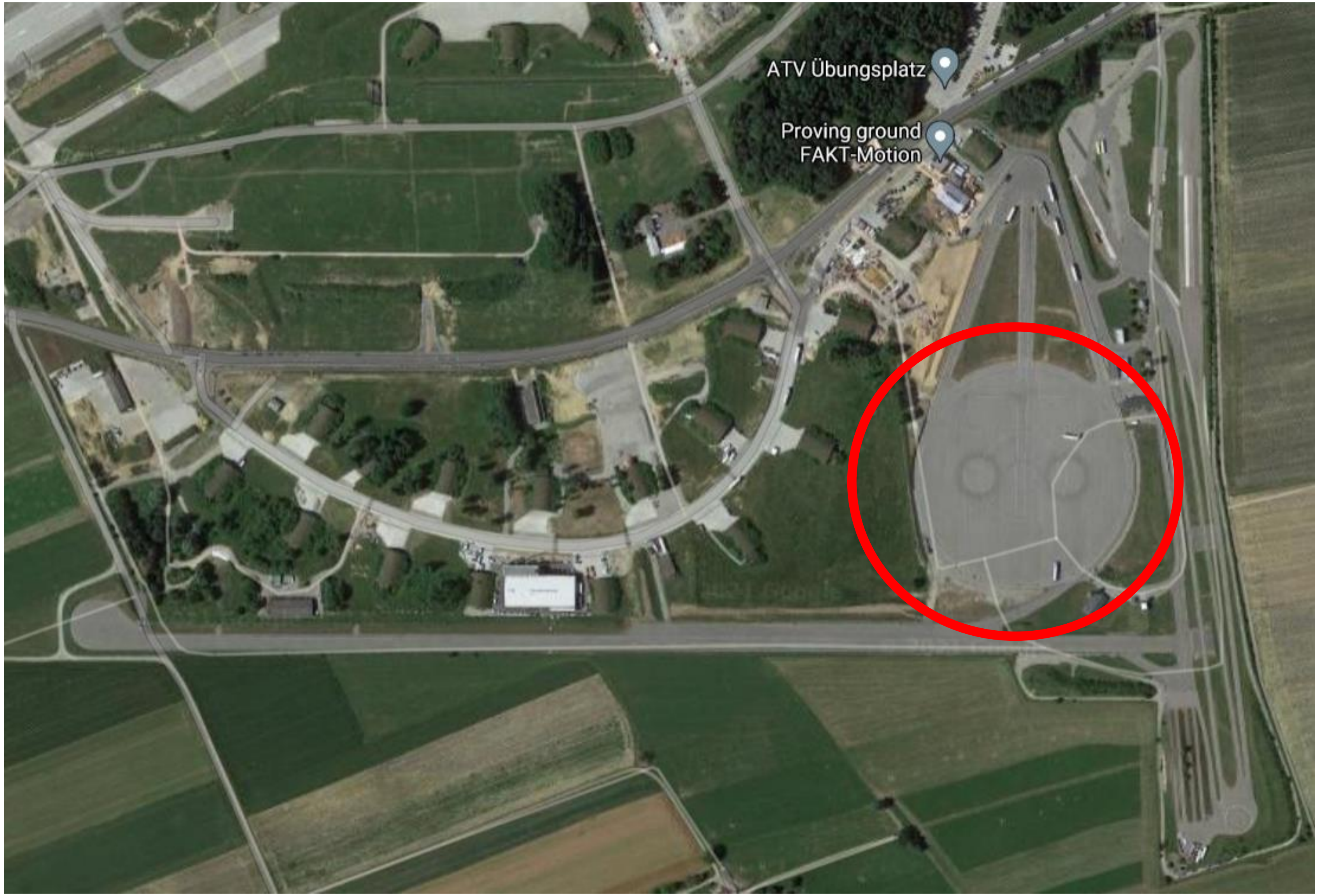


(b)



Haider, A.; Pigniczki, M.; Köhler, M. H.; Fink, M.; Schardt, M.; Cichy, Y.; Haas, L.; Zeh, T.; Poguntke, T.; Jakobi, M.; Koch, A.W. *Development of High-Fidelity Automotive LiDAR Sensor Model with Standardized Interfaces. Under review in Sensors 2022*

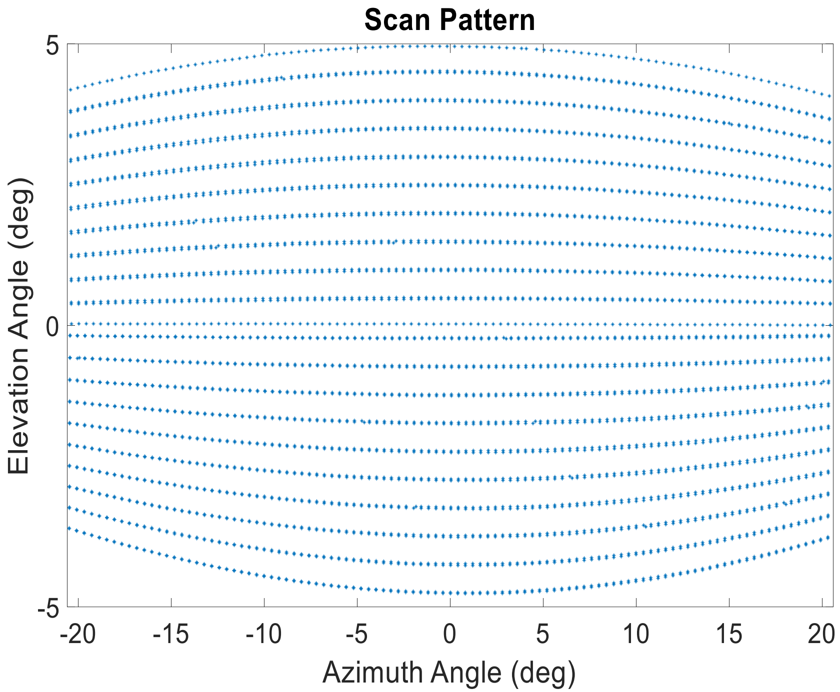
Proving Ground FAKT Motion in Benningen

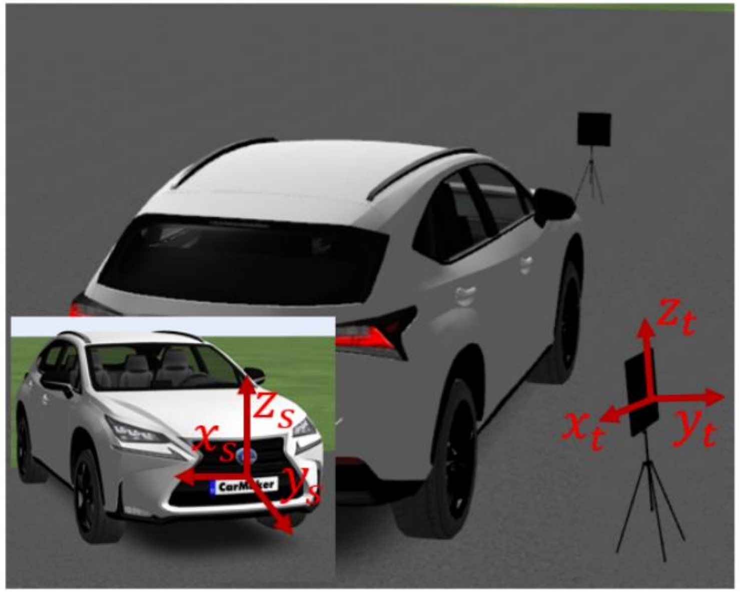


Static Test setup for Proving Ground (Real Environment) Measurement and Virtual Environment Results

Audi Q5:

- Blickfeld LiDAR Cube 1 (250 m range, FOV: +/-36 deg azimuth, +/-15 deg elevation)
- ADMA-G-PRO+ GPS with range accuracy of 0.1 m. (reference sensor)



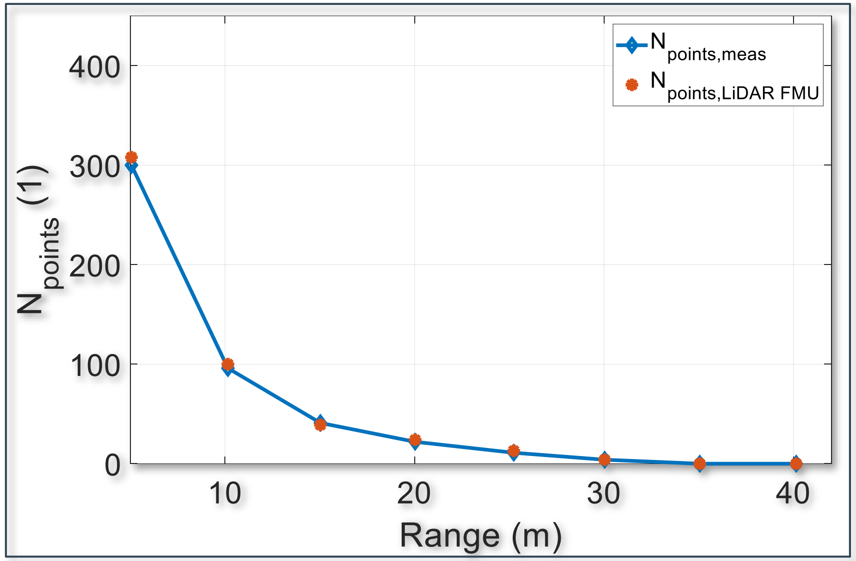


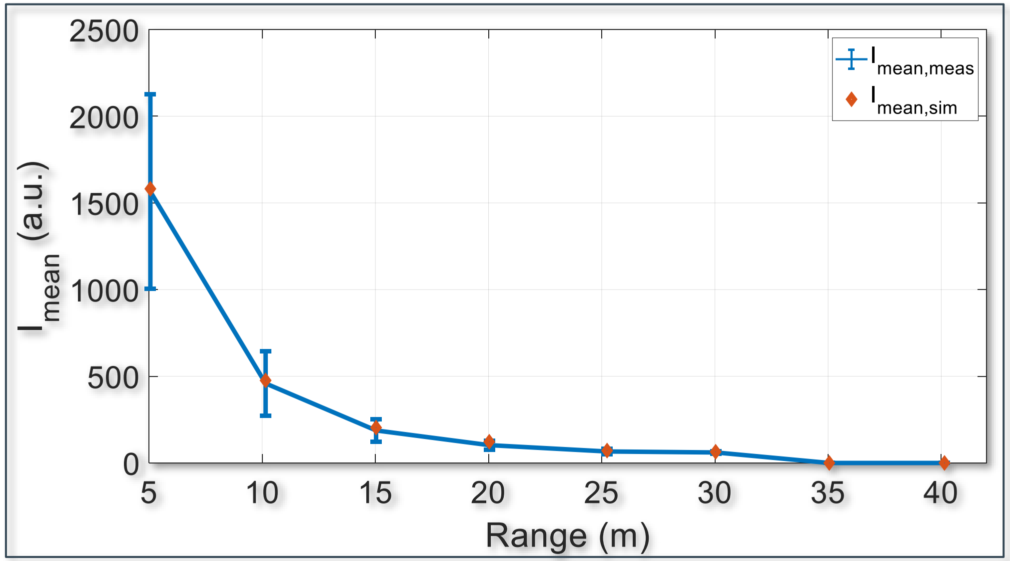
- FOV (42° Horizontal and 10° Vertical), 40 scan lines and 0.4° angle spacing, max. detection range 250 m, min. detection range 2 m

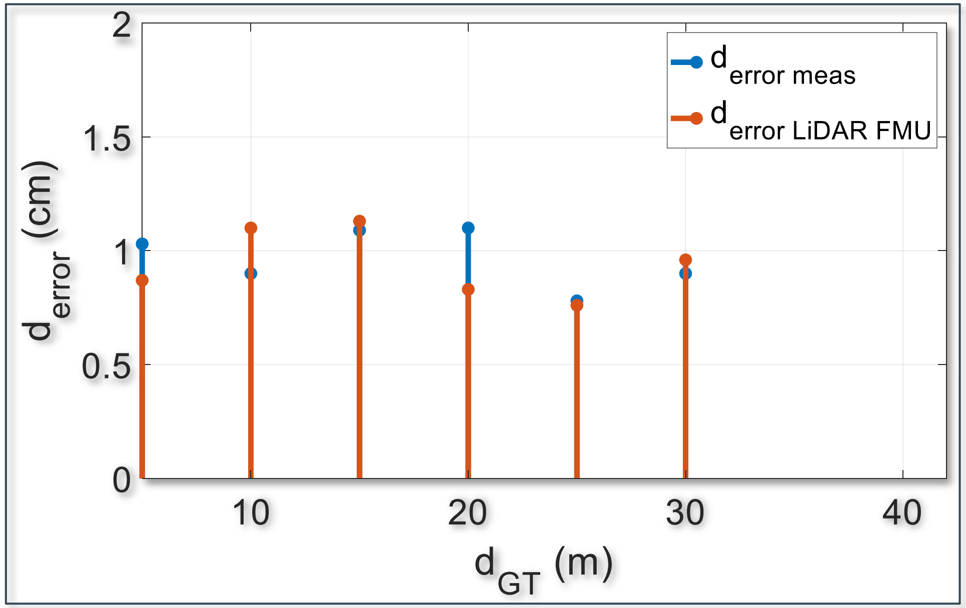
- Cube 1 position (in-vehicle coordinates) was X: 4073mm, Y(in driving direction right): 346 mm, Z: 490 mm

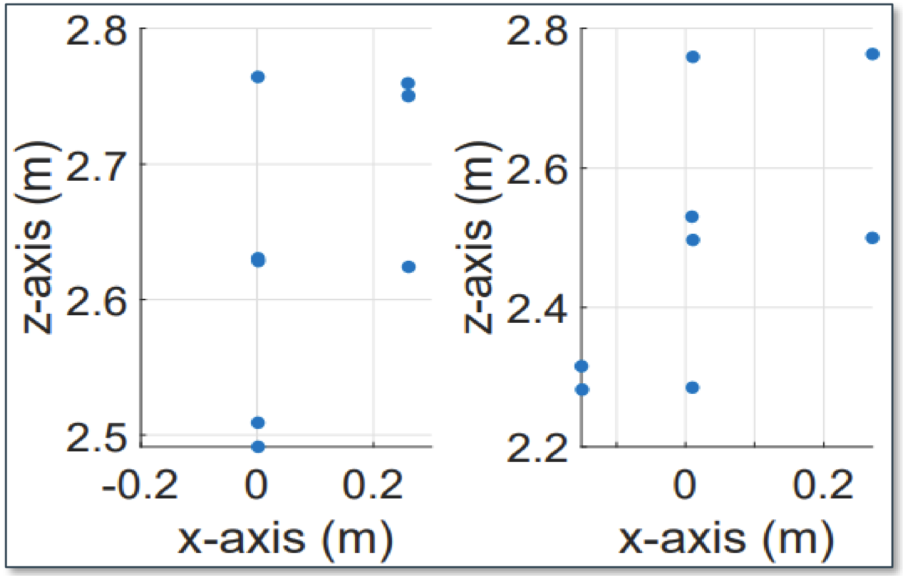
Haider, A.; Pigniczki, M.; Köhler, M. H.; Fink, M.; Schardt, M.; Cichy, Y.; Haas, L.; Zeh, T.; Poguntke, T.; Jakobi, M.; Koch, A.W. Development of High-Fidelity Automotive LiDAR Sensor Model with Standardized Interfaces. Under review in Sensors 2022

Proving Ground Measurements and Simulation comparison







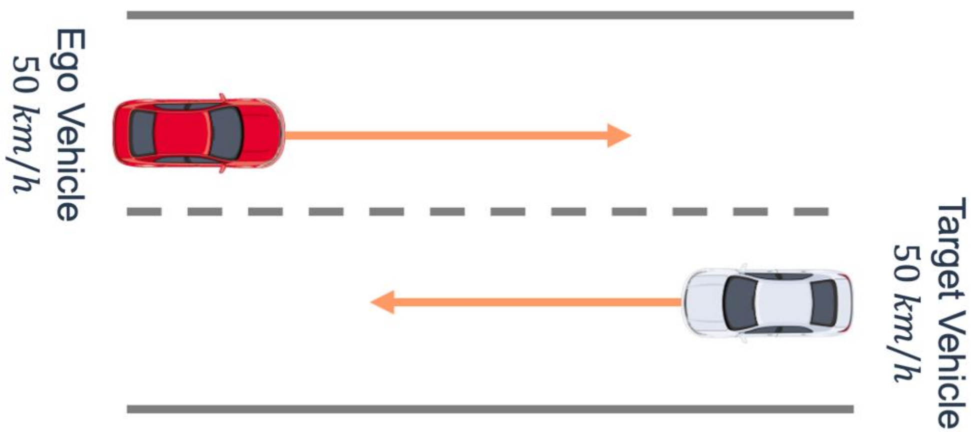


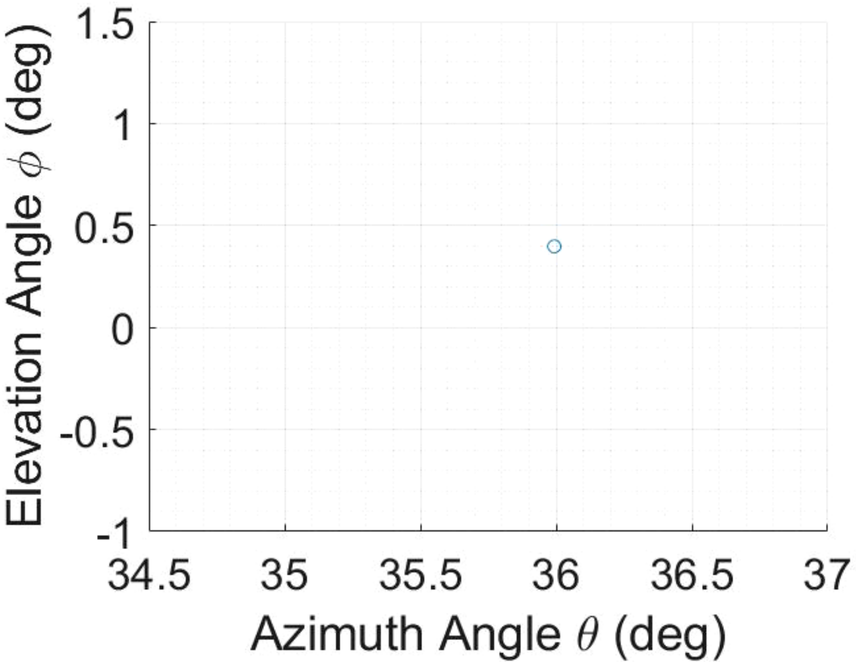
Cube 1 point clouds LiDAR FMU point clouds

- The sunlight was recorded $8\ klux$ and we have modeled it.
- The sunlight irradiance values are taken from the ASTM G173-03 standard.
- The MAPE for the I_{mean} is 11.1%
- The distance error is less than 2 cm
- The Cube 1 and LiDAR FMU is able to detect the target till $30\ m$
- The MAPE for the N_{points} is 9.6%

National Renewable Energy Laboratory, Reference Air Mass 1.5 Spectra: ASTM G-173. Available online: https://www.nrel.gov/ 503 grid/solar-resource/spectra-am1.5.html.

Proving Ground Dynamic Tests Setup: (Real Environment) Measurement and Virtual Environment Results



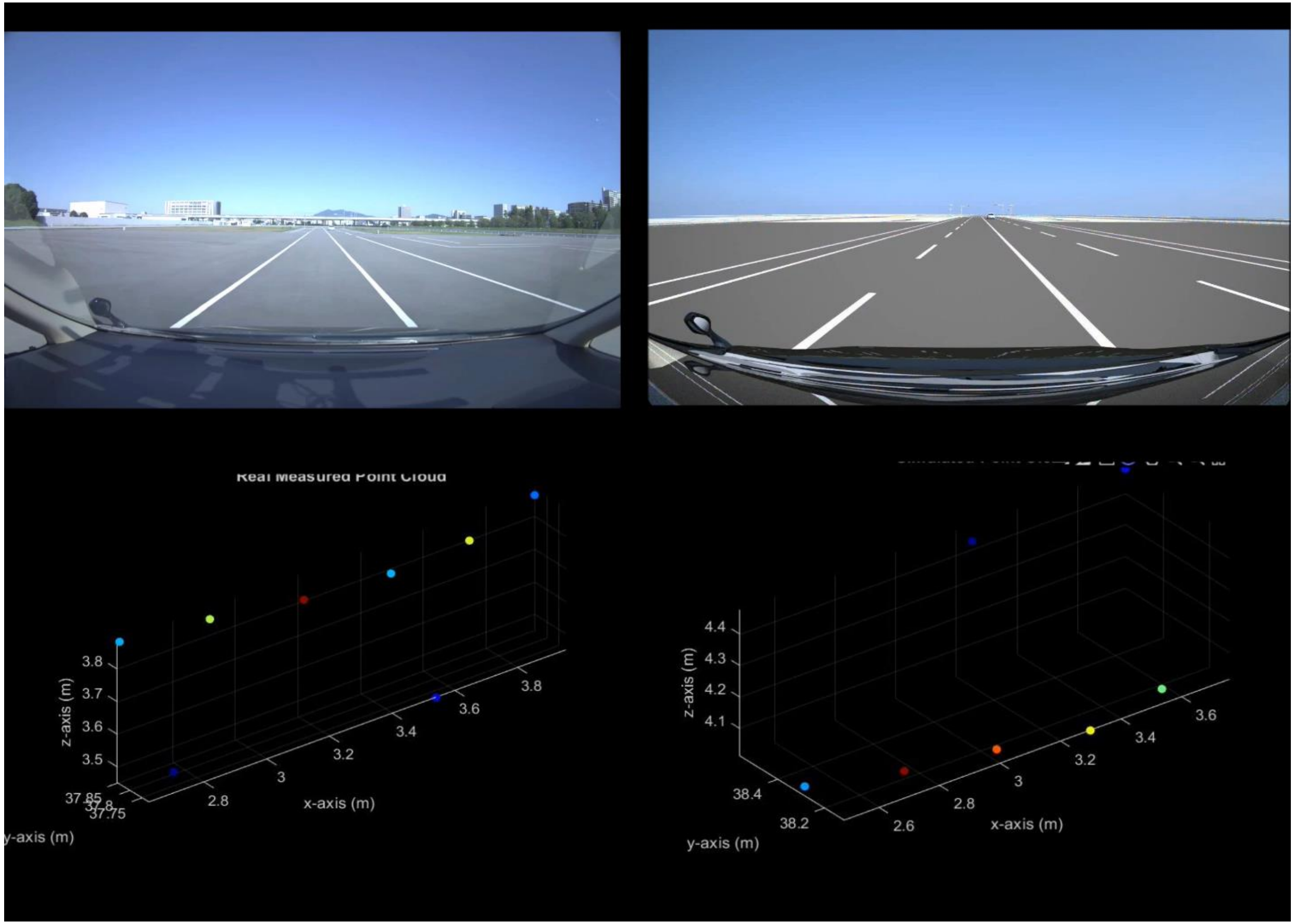


https://www.jari.or.jp/en/test-courses/jtown/46112/

Blickfeld Cube 1 scan pattern:

100 scan lines (50 scan line up and 50 down), FoV 72°horizontal and 30°vertical frame rate 5.4 Hz

Proving Ground Dynamic Tests: (Real Environment) Measurement and Virtual Environment Results

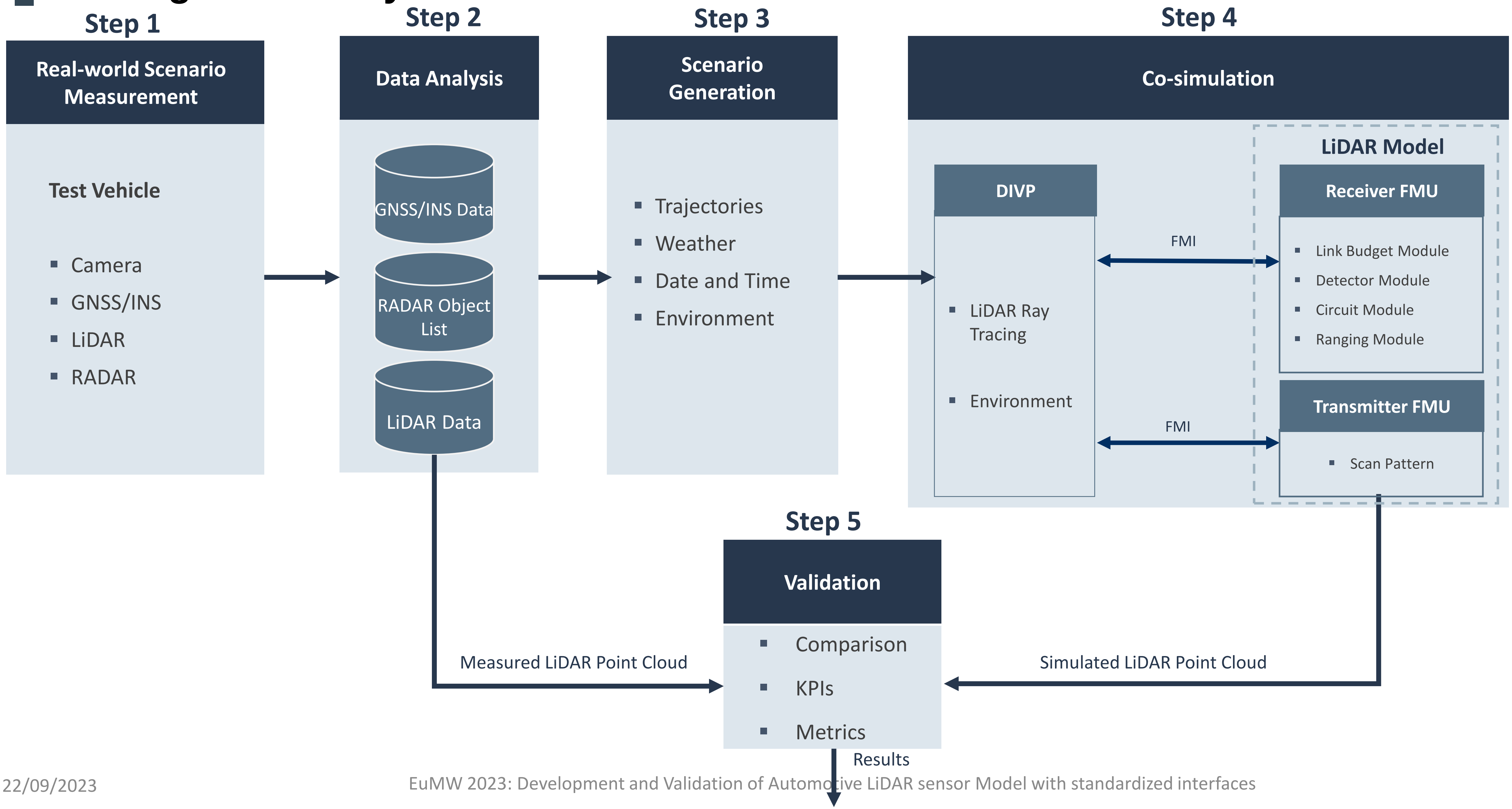


Blickfeld Cube 1 scan pattern:

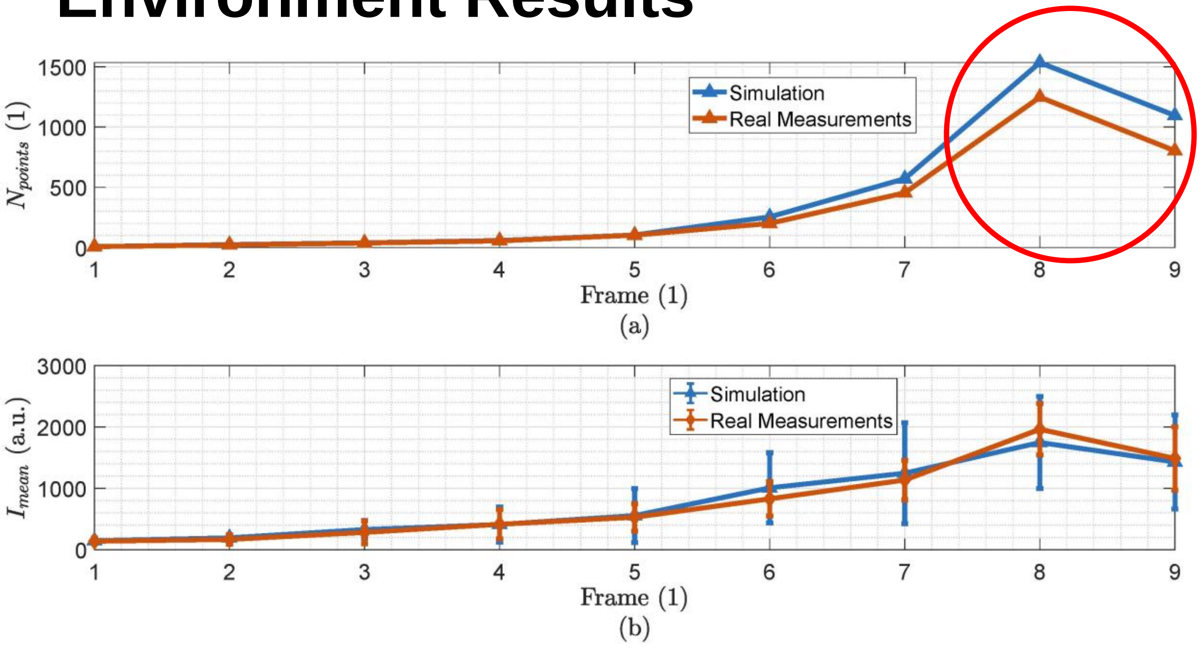
40 scan lines 50 scan line up and 50 down, FoV 72°horizontal and 30°vertical frame rate 5.4 Hz

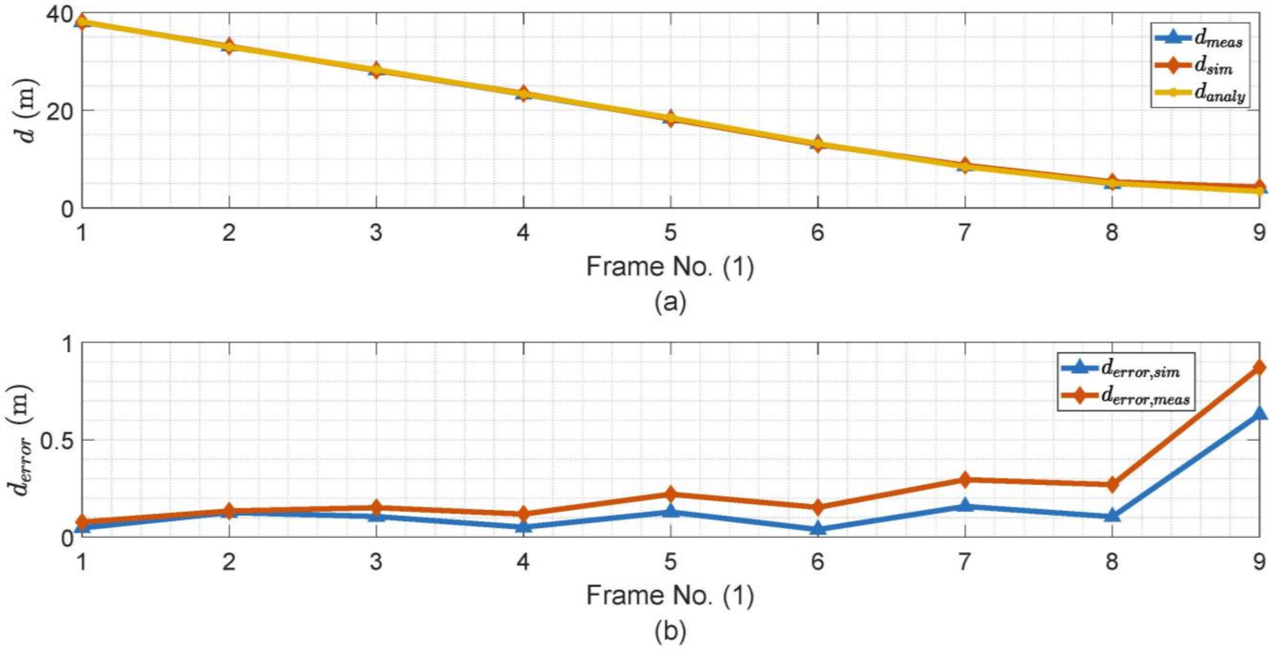
Relative speed is 100 km/h

Proving Ground Dynamic Tests: Validation Toolchain



Proving Ground Dynamic Tests: (Real Environment) Measurement and Virtual Environment Results





- Orientation of the object in simulation and real measurement is different for 8th, and 9th frame
- The MAPE for the N_{points} is 13.2%
- The MAPE for the I_{mean} is 9.2%
- The distance error d_{error} is $0.08\ \%$

Proving Ground Dynamic Tests: (Real Environment) Measurement and Virtual Environment Results

Metrics Applied on 2-D (yx, xz) Occupancy Grid Map

- We used Baron‘s[1] cross correlation and occupied cell ratio (OCR) [2] metric to quntify the difference between the simulation and real measurements
- Baron‘s correlation is applied on **Probability occupancy grid** and OCR is applied on **Binary occupancy grid map**

$$C_B = \frac{\langle SG.RG\rangle - \langle SG\rangle\langle RG\rangle}{\sigma(SG)\,\sigma(RG)}$$

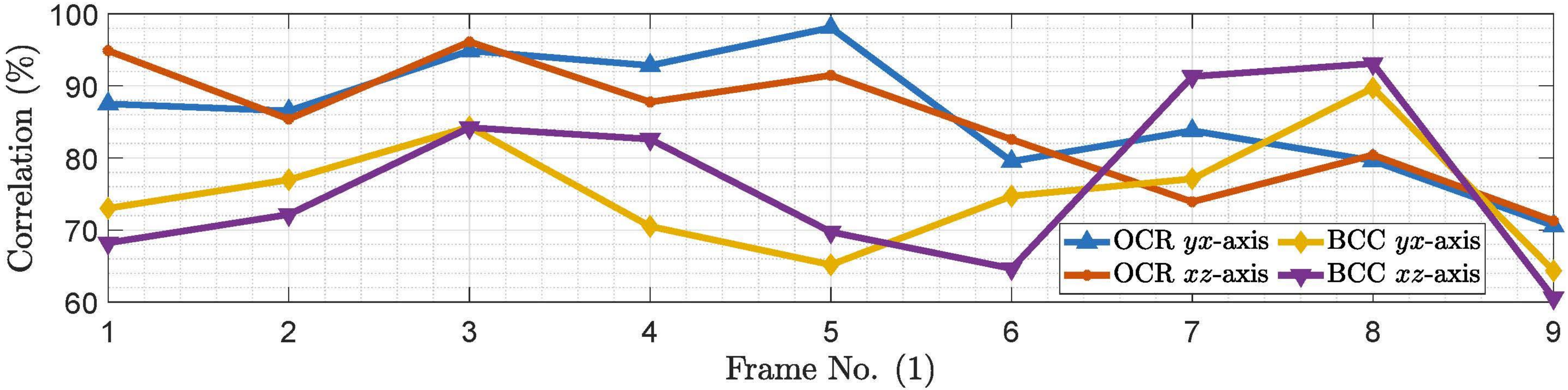
$$\mathrm{OCR} = \frac{\sum cells_{sim\,map,\,occ,\,true}}{\sum Cells_{real\,map,occ,true}}$$

C_B is Barons cross correlation
$\langle RG\rangle$ is OG from real data
$\langle SG\rangle$ is OG from real data

The OCR is the ratio between the true cells classified as occupied (cells which are occupied in the simulated map and the real map) in the simulated map and the total number of occupied cells (OCC) in the real map

[1]T. 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
[2]R. 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.

Proving Ground Dynamic Tests: (Real Environment) Measurement and Virtual Environment Results



- OCR Metric is less sensitive to the scenario modeling as compared to the Baron’s correlation metric
- The frames for which the simulated and real object's orientation, position, and velocity match well the correlation is high for those frames
- Mean similarity of OCR metric is 86.1% for the yx axis and 84.8% for xz axis
- Mean similarity of BCC metric is 75.1% for the yx axis and 76.3% for xz axis

Conclusion and Outlook

- We can develop a high-fidelity ray tracing-based LiDAR model by using standardized interfaces
- LiDAR sensor model performance highly depends on environmental modeling
- The simulation and real measurements will match well if the simulated objects position, orientation and speed will be similar to the real world objects

Outlook

- Rain and fog effects on the performance of automotive LiDAR sensors will be modeled and validated