NAGOYA UNIVERSITY

Research statements

Towards a hyperspectral and scalable digital twin

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Biography

NAGOYA UNIVERSITY

Quang Nhat Nguyen

- Master of Engineering in **Electrical Engineering**
  10.2021 – 9.2023, Nagoya University, GPA: 4.0/4
- Bachelor of Engineering in **Electrical Engineering, Electronics, and Information Engineering**
  10.2017 – 9.2021, Nagoya University, GPA: 3.94/4, Valedictorian
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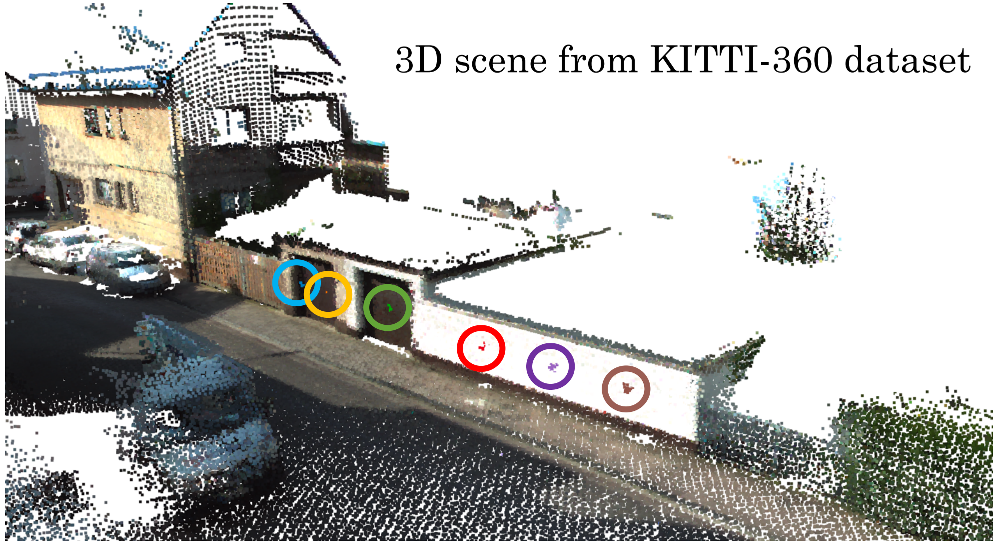
Research experiences

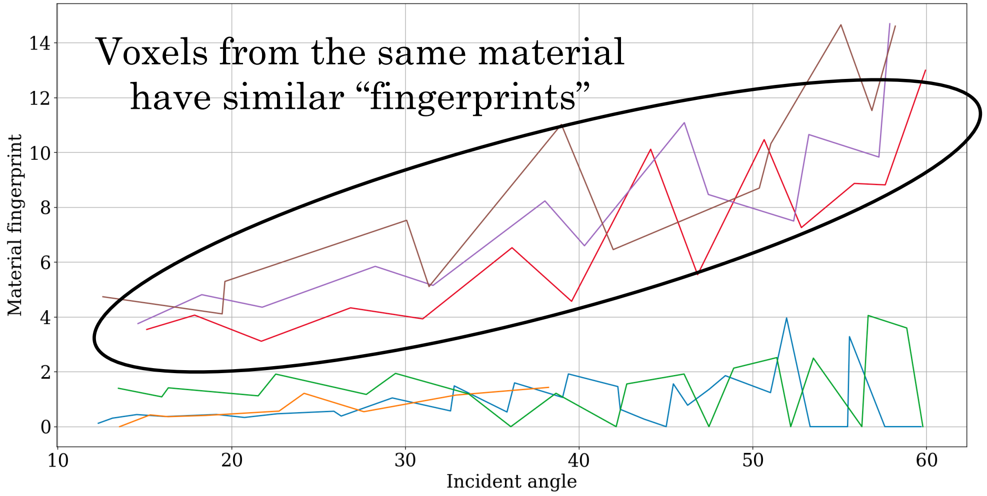
- 10.2018 – 3.2020: **Graduate School of Mathematics**, Nagoya University
  Research on spectral theory and functional analysis. Journal article published in *Adv. Oper. Theory* (2020).
- 4.2020 – present: **Takeda Lab**, Dept. of Intelligent Systems, Nagoya University
  Research on **perception** of intelligent vehicles. First-author paper published in *FAST-zero* (2021).
- 11.2021 – 3.2022: **JARI** (Japan Automobile Research Institute)
  Research on Unreal Engine's LiDAR simulation module based on Physics.
- 4.2022 – present: **NEDO** (New Energy and Industrial Technology Development Organisation)
  Research on designing, calibrating, and synchronising a multimodal and multispectral data capturing system.
- 9.2022: **RIKEN Centre for Computational Science, Data Assimilation research group**
  Research on the LETKFCC (Local Ensemble Transform *Kalman Filter* with Cross Correlation).
- 4.2023 - present: **MapIV** (a group member of **TierIV**)
  Research on calibration, sensors fusion, 3D mapping, digital twin reconstruction.

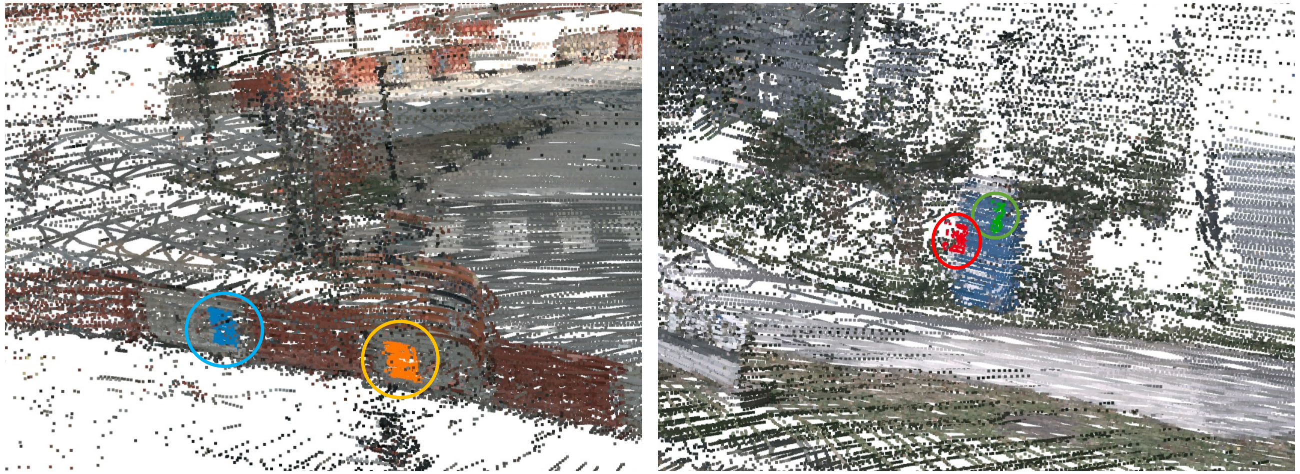
Awards

- **Valedictorian**
  Nagoya University School of Engineering
- **Outstanding Research Presentation**
  Nagoya University Grad. School of Engineering
- **Japan Government Scholar**
  MEXT, Japan Government

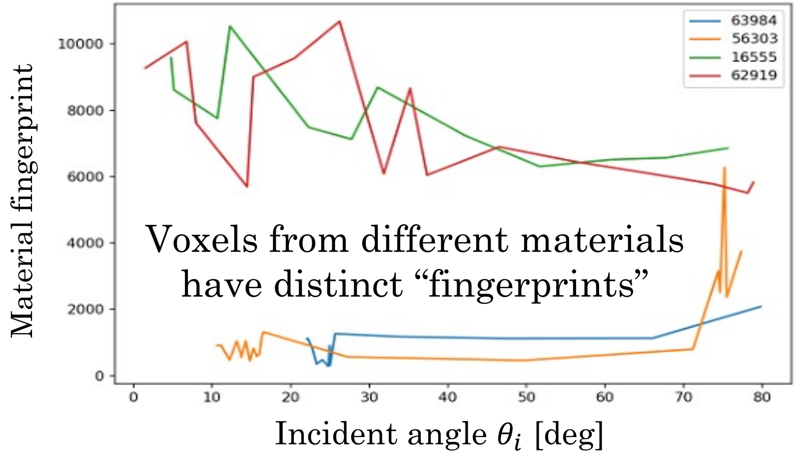
Material classification using “material fingerprint”





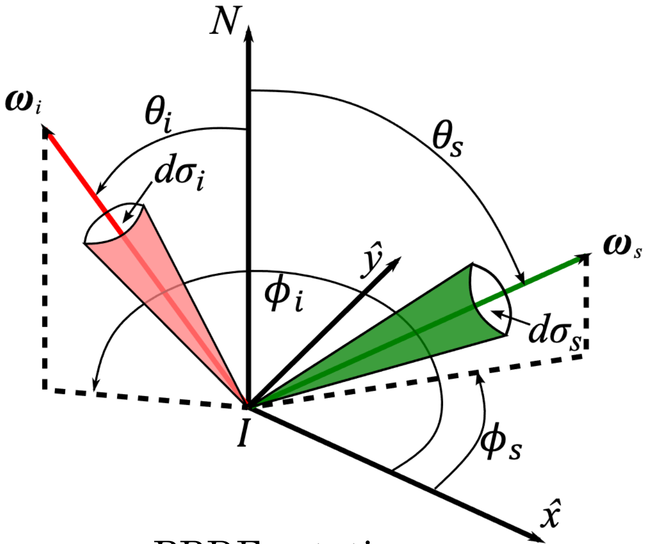


3D scene from nuScenes dataset

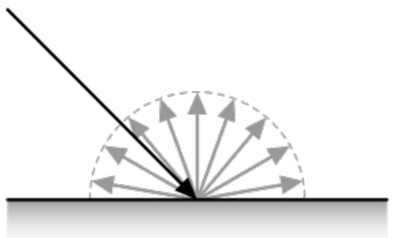


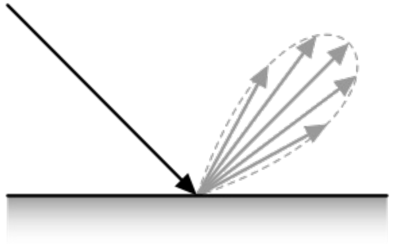
"Material fingerprint" theoretical basis

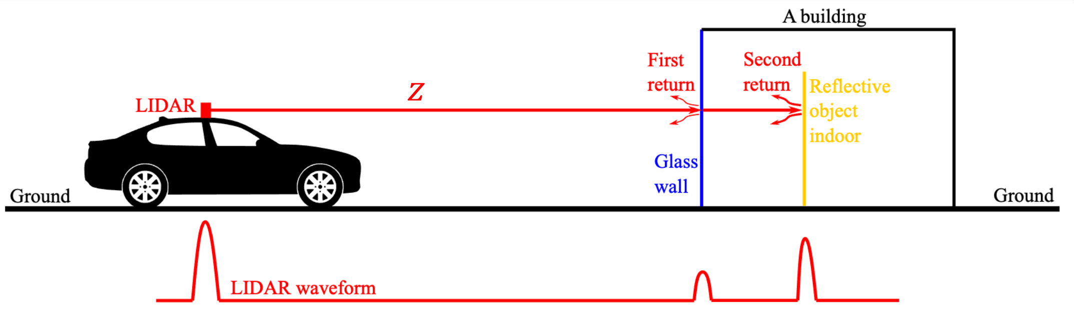
- **BRDF** (Bi-directional Reflectance Distribution Function) quantifies the **optical scattering characteristic** of each material:
$$f_r(\boldsymbol{\omega_i}, \boldsymbol{\omega_s}) = \frac{dL_s(\boldsymbol{\omega_s})}{dL_i(\boldsymbol{\omega_i})} = \frac{dL_s(\boldsymbol{\omega_s})}{L_i(\boldsymbol{\omega_i}) \cos\theta_i \, d\boldsymbol{\omega_i}}$$
- In case of a LiDAR sensor, the above eq. simplifies to:
$$L_s = \rho_m(\theta_i) \cos\theta_i \, L_i(\boldsymbol{\omega_i})$$
- The backscattering function $\rho_m(\theta_i)$ appears again in the LiDAR's intensity equation:
$$I_r(m, z, \theta_i) = E_l \frac{c\rho_m(\theta_i) \cos\theta_i \, A_r}{2z^2} \tau_T \tau_R \exp\left(-2 \int_0^z \alpha(z')dz'\right)$$
- In clear weather condition, it simplifies to:
$$I_r(m, z, \theta_i) = C_{const} \times \frac{\rho_m(\theta_i) \cos\theta_i}{z^2}$$
- The dependency on incident angle θ_i characterises the optical property of the material hit by LiDAR's laser beam. We call it "material fingerprint":
$$\mathcal{F}_m(\theta_i) = C_{const}\rho_m(\theta_i) \cos\theta_i$$
- It is obtained by decoupling LiDAR's intensity from distance z as:
$$\mathcal{F}_m(\theta_i) = I(m, z, \theta_i) \, z^2$$



BRDF notations

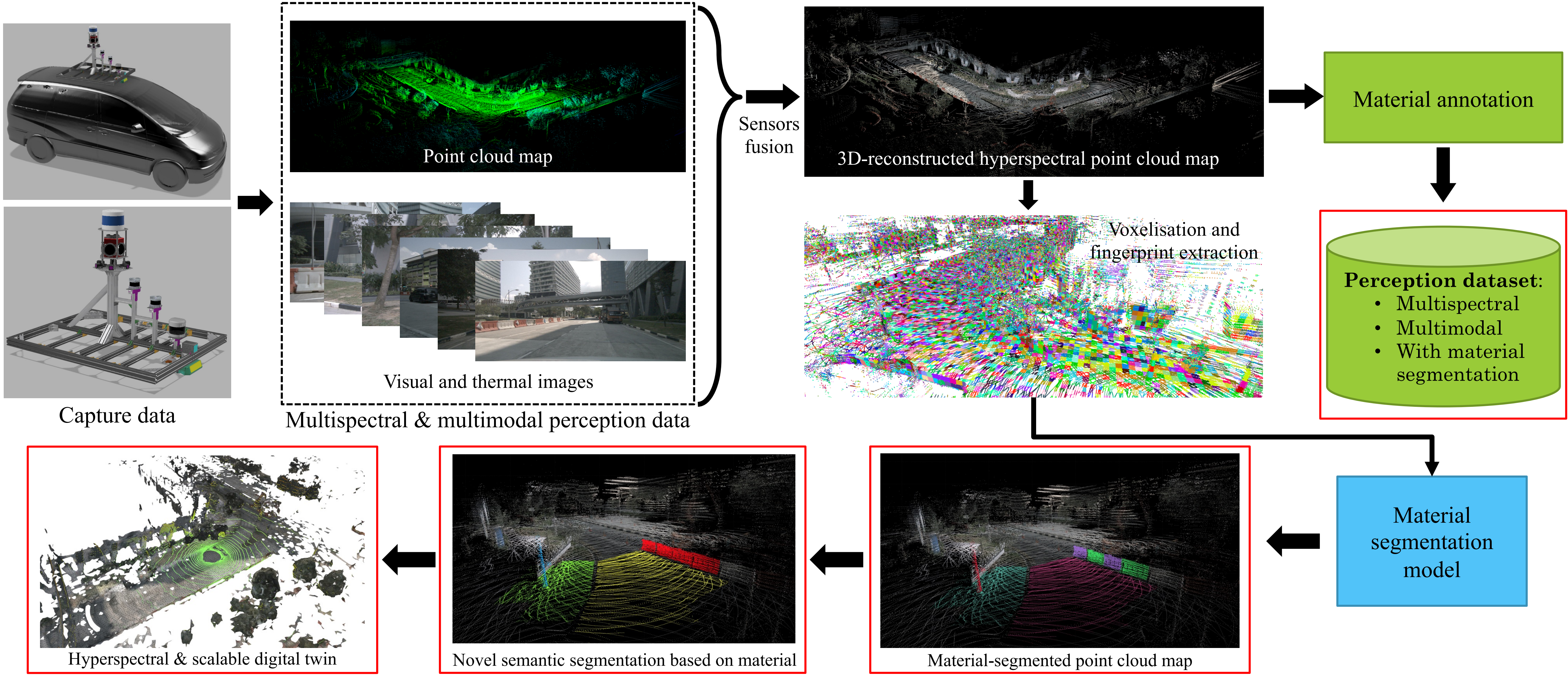

Diffusive


Glossy



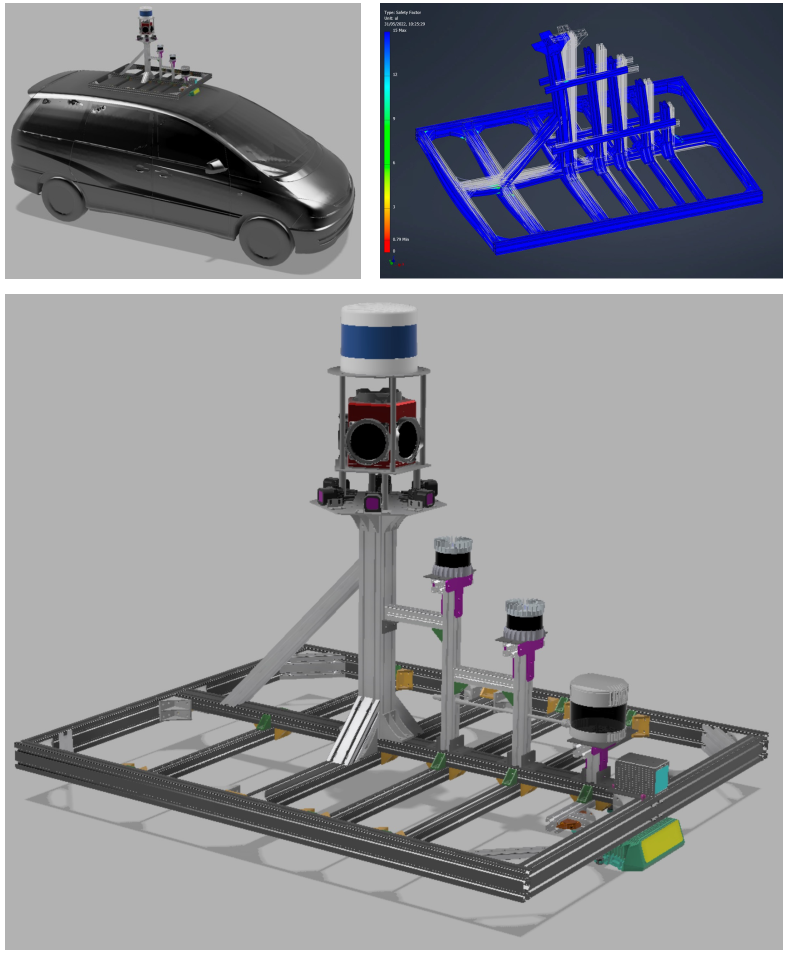
Transmission and remission of a LiDAR's laser beam

Four objectives of my current research

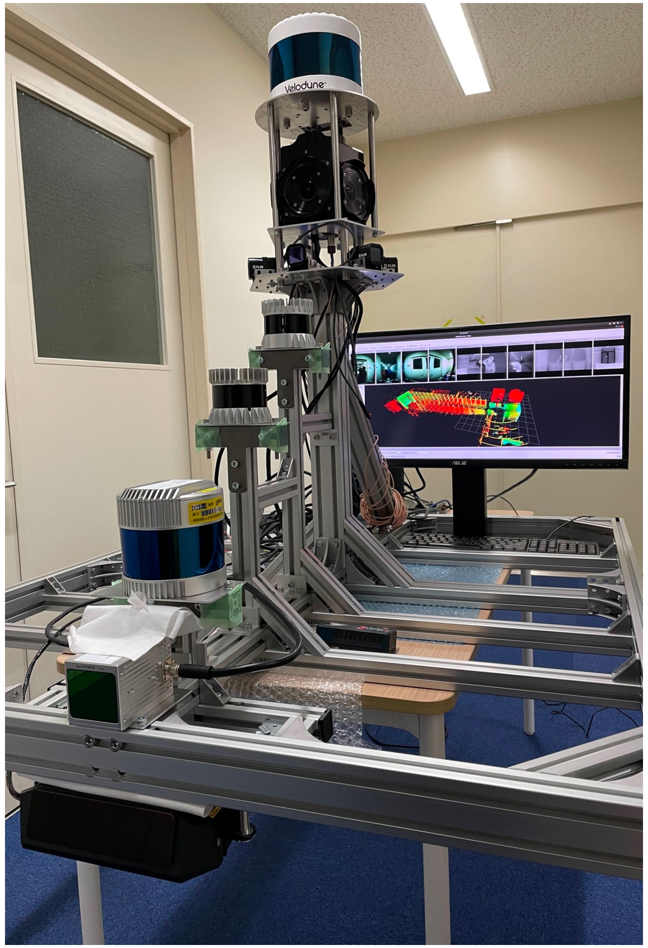


Work in progress, will be submitted for publication in ITSC 2023

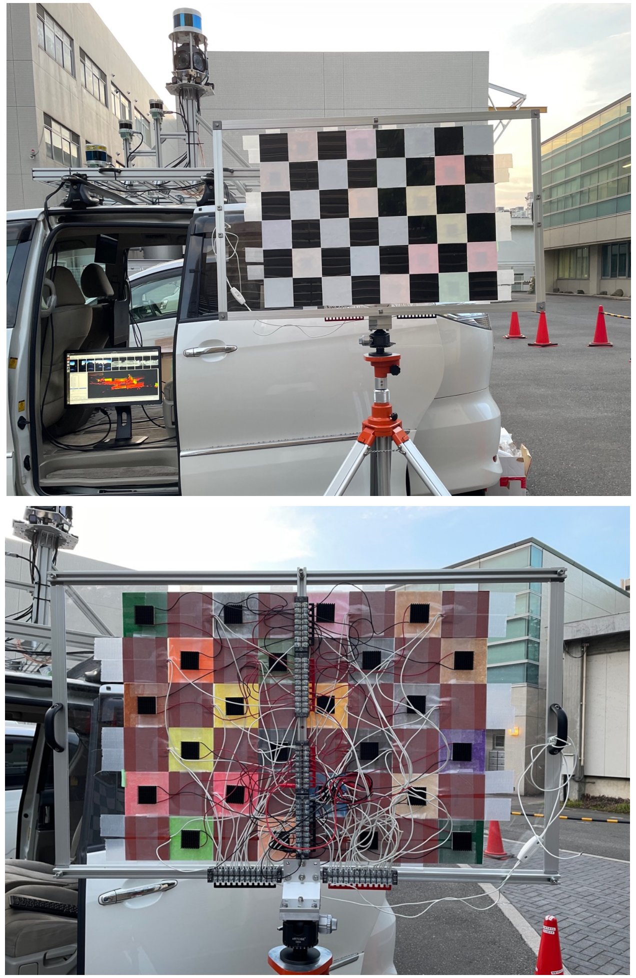
Engineering a multispectral & multimodal sensing system



3D CAD and structural analysis



Assembly, ROS implementation, synchronisation

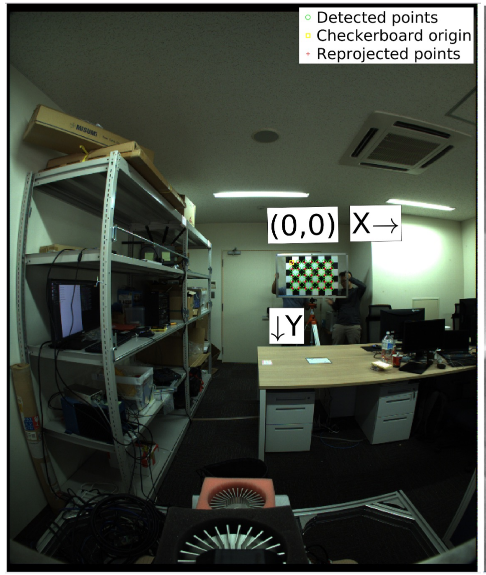


Calibration

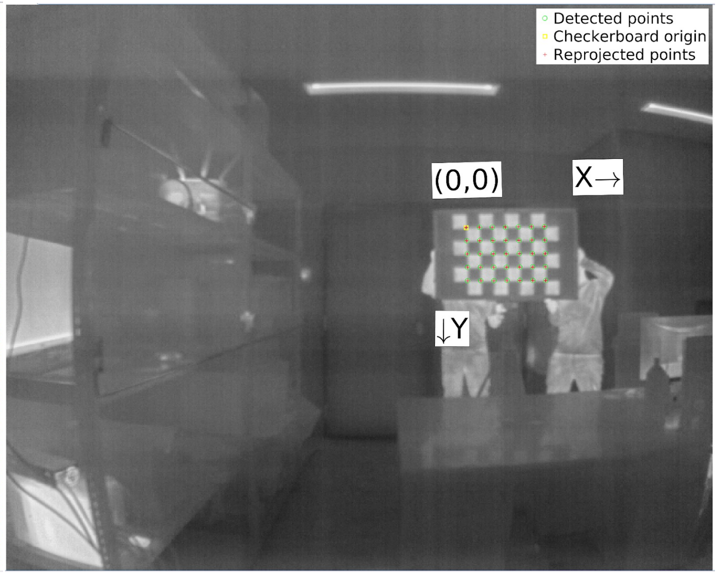
Multispectral and multimodal instrumented vehicle

Modality	Manu-facturer	Model name	Qty	Spectral band	HFOV	VFOV	No. of channels
Camera	Teledyne	Ladybug5	1	Visual spectrum	360°	103°	N/A
Camera	Teledyne	FLIR ADK	6	LWIR spectrum (800-1400 nm)	75°	60°	N/A
LiDAR	InnoFusion	Falcon	1	FIR (1550nm)	120°	25°	≈400
LiDAR	Livox	Avia	1	NIR (905nm)	70.4°	77.2°	N/A
LiDAR	Hesai	Pandar64	1	NIR (905nm)	360°	40°	64
LiDAR	Ouster	OS1-128	1	NIR (850nm)	360°	40°	128
LiDAR	Ouster	OS1-64	1	NIR (850nm)	360°	33.2°	64
LiDAR	Velodyne	VLS-128	1	NIR (903nm)	360°	40°	128

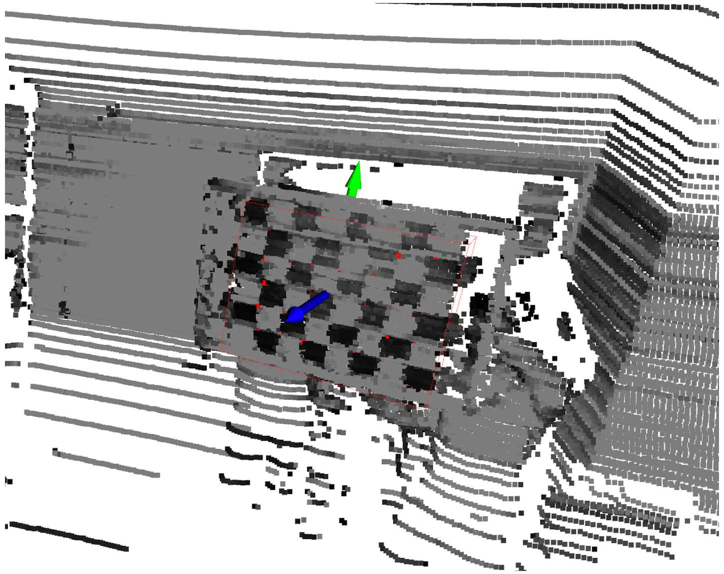
Joint calibration target for multiple sensor modalities



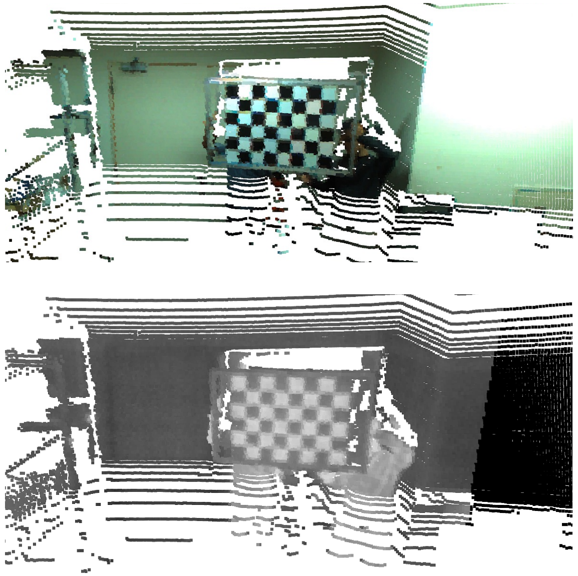
RGB image from Ladybug5



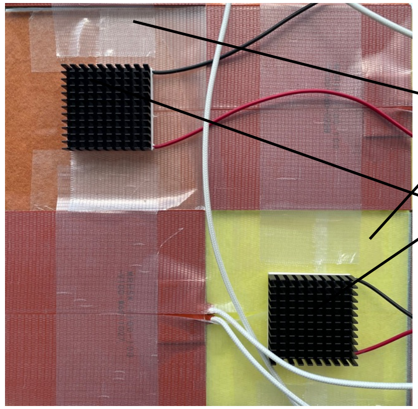
Thermal image from FLIR ADK camera



Automatic chessboard detection from VLS-128 point cloud intensities



LiDAR-camera fusion from calibration results



White paper layer

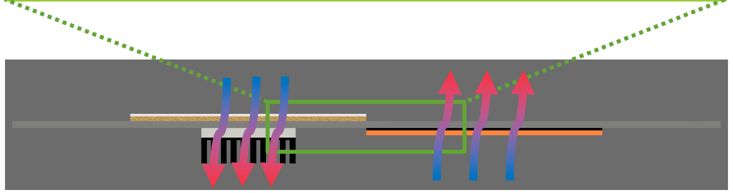
Felt layer (for thermal insulation)

Acrylic base (transparent)

Peltier-effect heat pump (for cooling)

Black aluminium plate (for uniform heat distribution)

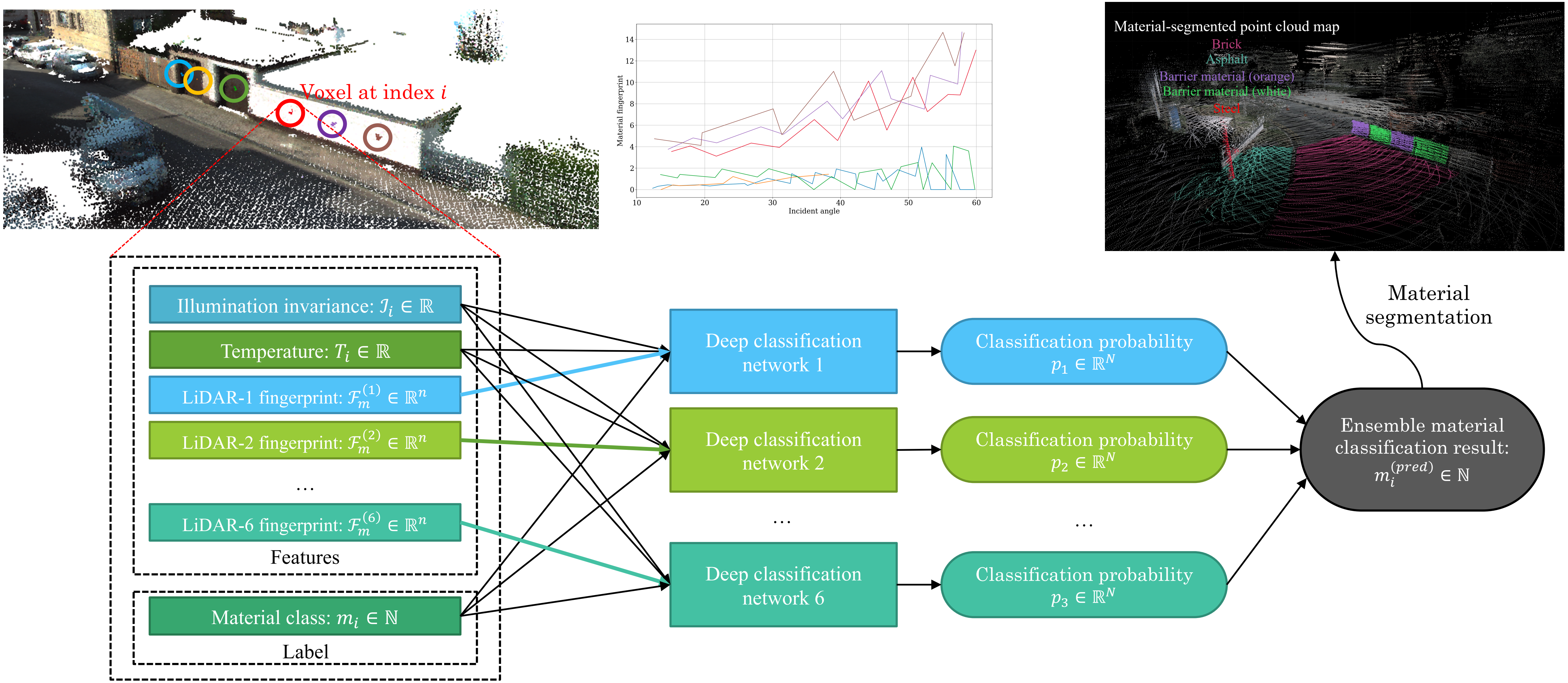
Silicone heating pad



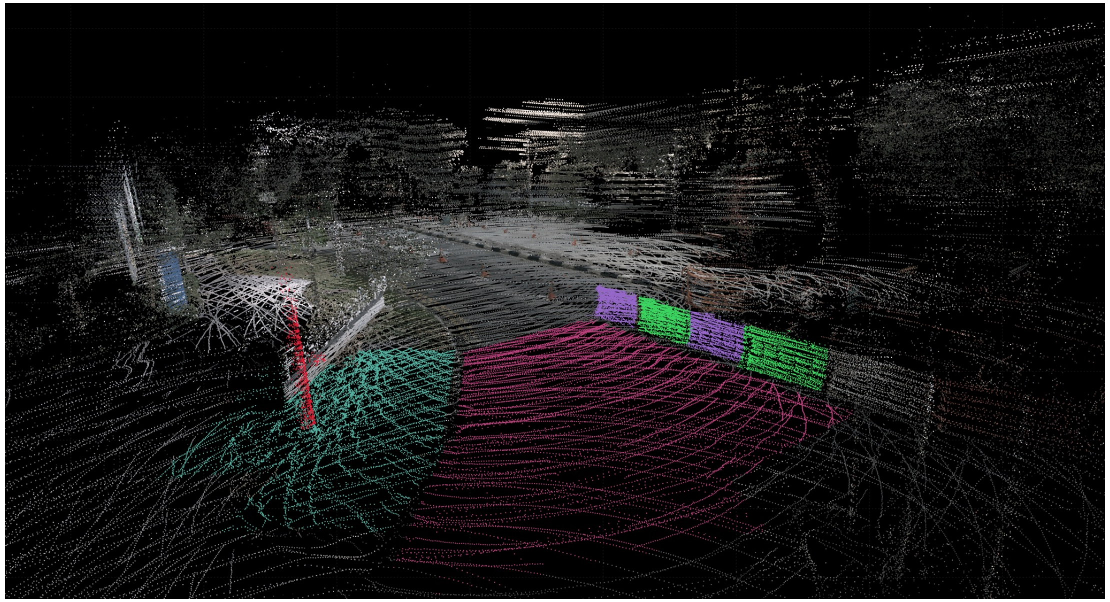
Cross-section layers structure (zoomed out)

Work in progress, will be submitted for publication in ITSC 2023

Material segmentation deep learning model



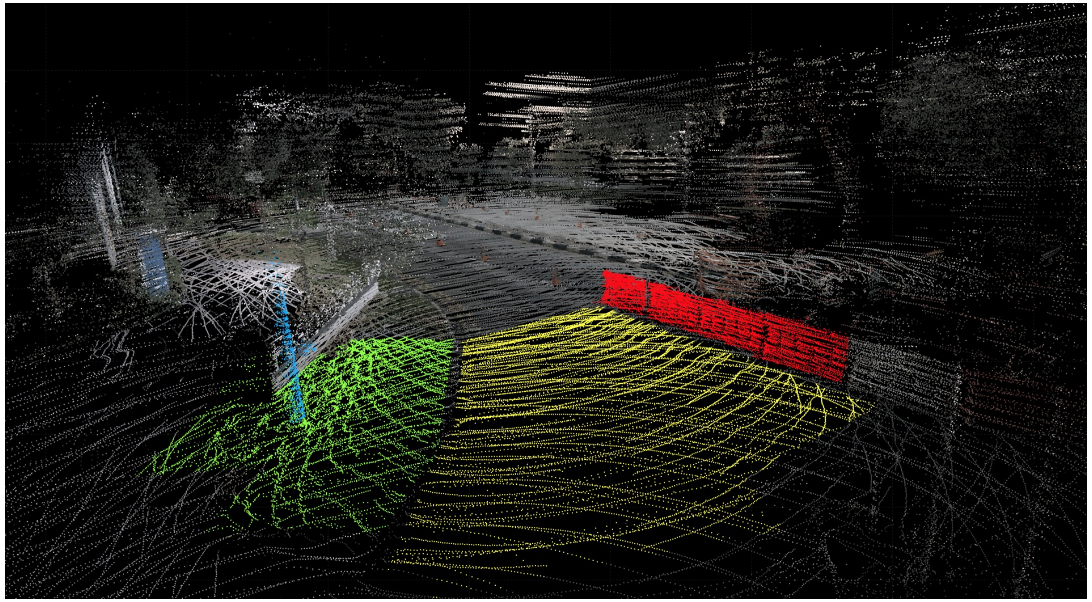
Target result



Material-segmented point cloud map
Brick
Asphalt
Barrier material (orange)
Barrier material (white)
Steel

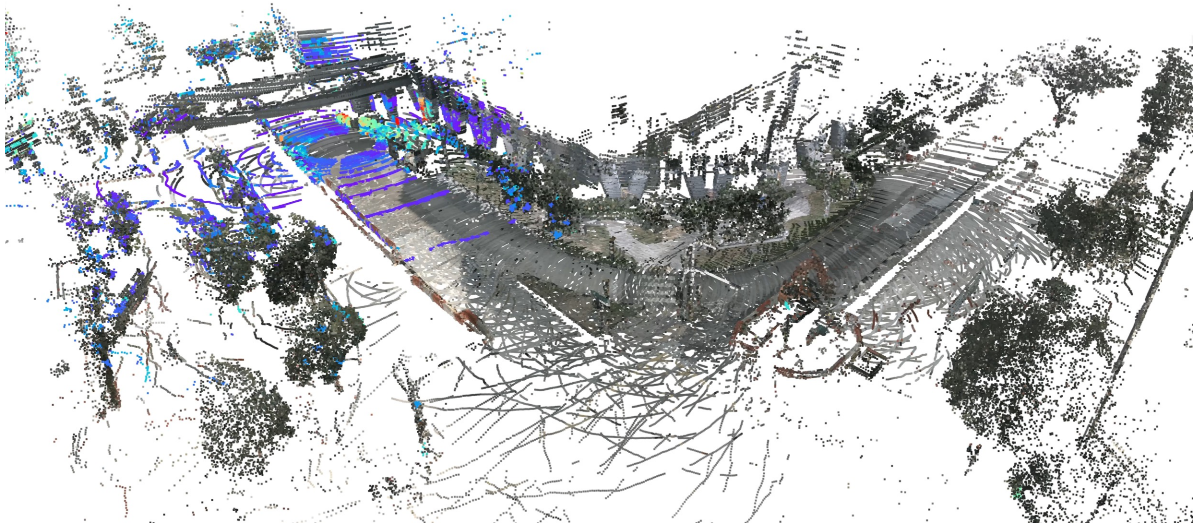
Geometric information
Horizontal surface
Horizontal surface
Vertical surface
Vertical surface
Vertical cylinder

Novel semantic segmentation model

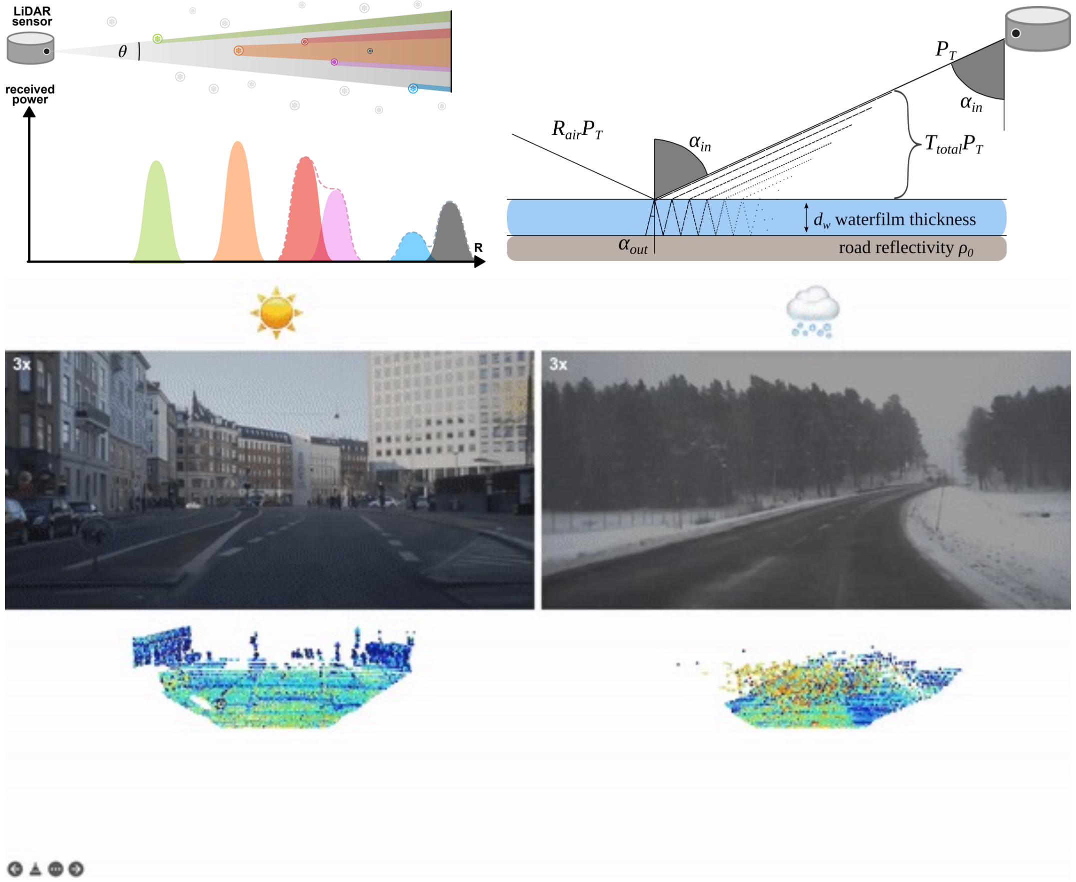


Novel semantic segmentation based on material
Pavement
Road
Obstacle
Traffic sign’s pole

Future developments



Photorealistic and scalable LiDAR **intensity** simulation in the hyperspectral and scalable **digital twin**
(3D scene from NUSCENES dataset)



Physics-based weather synthesis in **simulation environment**
(Hahner et al, CVPR'22)

Appendix: Data assimilation research at RIKEN CCS

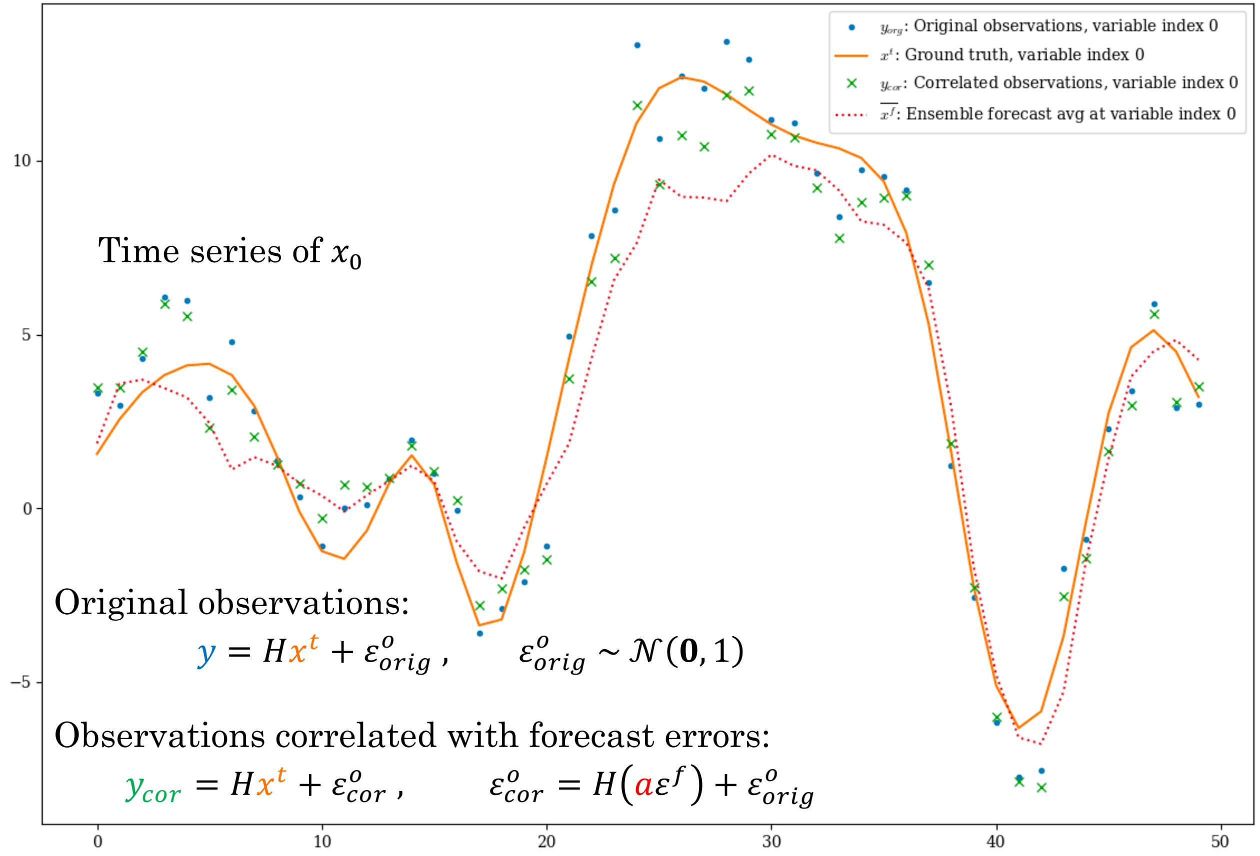
- I derived the following equations for the LETKFCC (Local Ensemble Transform Kalman Filter with Cross Correlation):

$$x^{a(i)} = \overline{x^f} + X^f_{orig}\left\{(1-a)\widetilde{P_a}\left(Y^f_{orig}\right)^T\left(R_{orig}\right)^{-1}\left(y_{cor} - H\overline{x^f}\right) + W^{(i)}\right\}$$

$$\widetilde{P_a} = \left\{\frac{(N-1)}{\rho}I + (1-a)^2\left(Y^f_{orig}\right)^T\left(R_{orig}\right)^{-1}Y^f_{orig}\right\}^{-1}$$

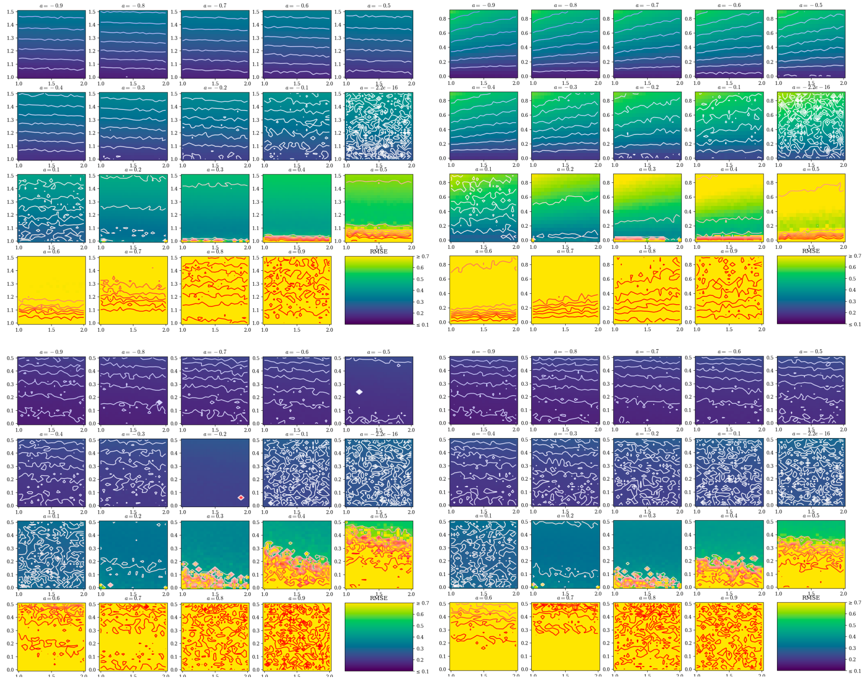
$$W = \left[(N-1)\widetilde{P_a}\right]^{1/2}$$

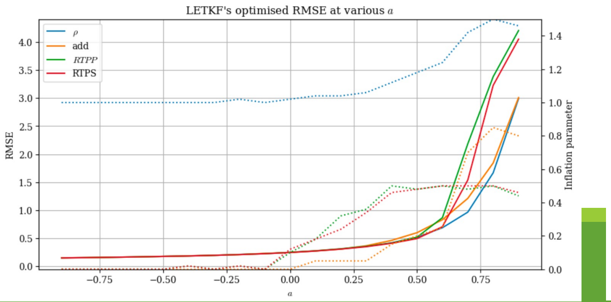
Correlated observations vs. original observations, $a = 0.5$

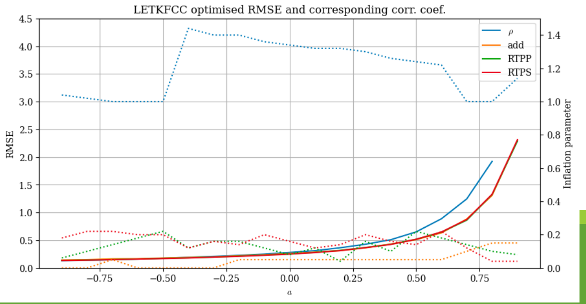


- I implemented parallel computation of many large-scale data assimilation experiments on the Fugaku supercomputer.

- Through the experiments, I investigated the impacts of the cross-correlated observations on the accuracy of the LETKF and LETKFCC.







Thank you!