NAGOYA UNIVERSITY

Research experiences

Quang Nhat Nguyen

Department of Electrical Engineering
Graduate School of Engineering, Nagoya University

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Biography

NAGOYA UNIVERSITY

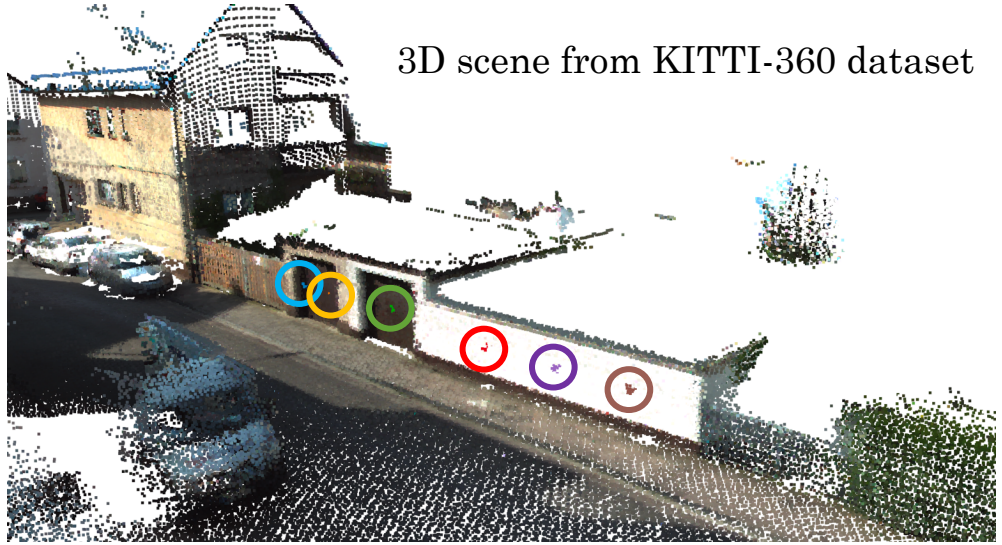
Quang Nhat Nguyen

- Date of birth: 27 November 1999 (23)
- Department of Electrical Engineering
  Graduate School of Engineering, Nagoya University
- nguyen@g.sp.m.is.nagoya-u.ac.jp

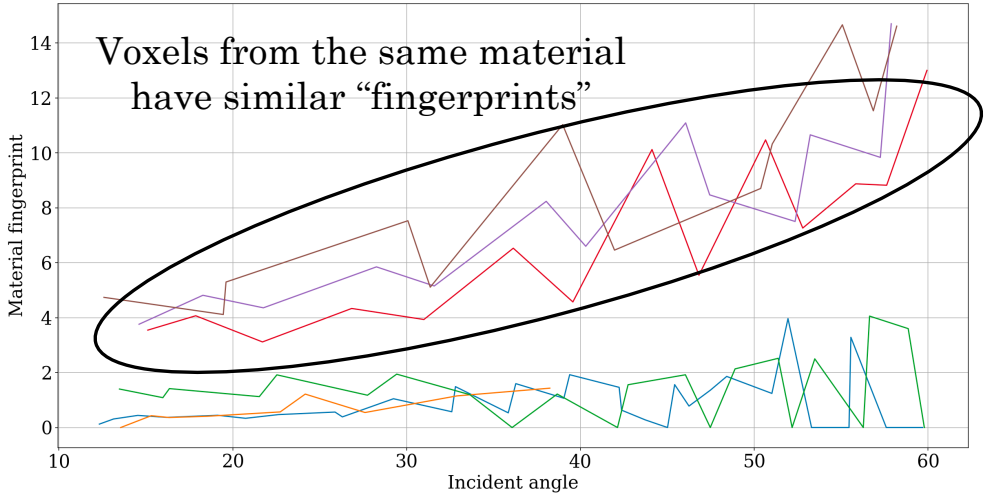
Research experiences

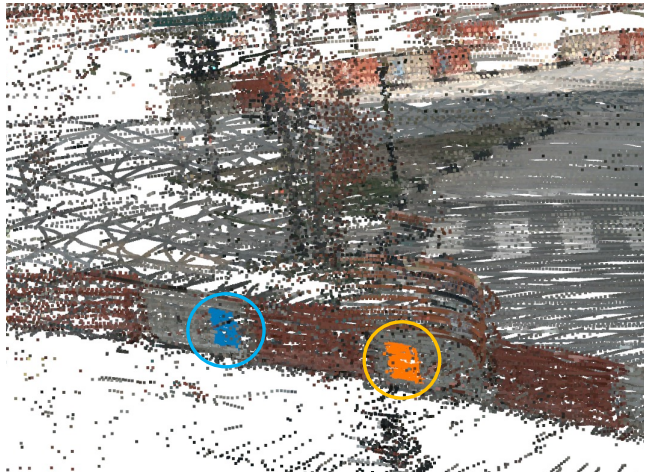
- 10.2018 – 3.2020: **Graduate School of Mathematics**, Nagoya University
  Research on spectral theory and functional analysis. Journal article published in *Adv. Oper. Theory* (2020).
- 4.2020 – 9.2021: **Takeda Lab**, Dept. of Intelligent Systems, Nagoya University
  Research on Physics-based LiDAR waveform simulation. First-author paper published in *FAST-zero* (2021).
- 10.2021 – Present: **Takeda Lab**, Dept. of Intelligent Systems, Nagoya University
  Research on material classification from multispectral and multimodal perception data.
- 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).

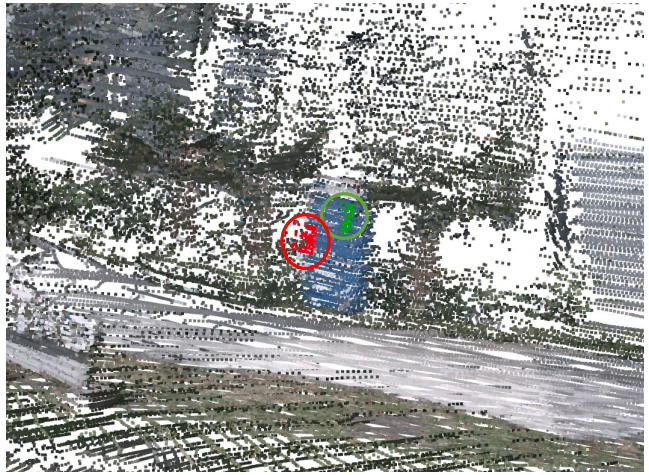
Material classification using “material fingerprint”



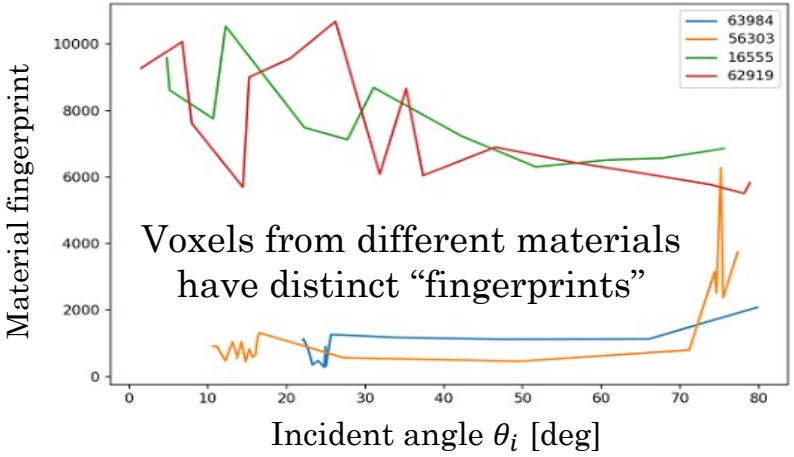
3D scene from KITTI-360 dataset







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:

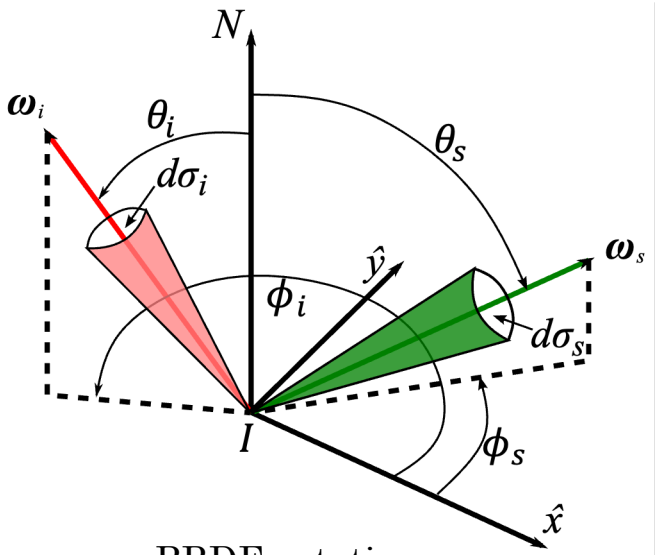
$$I_r(m, z, \theta_i) = C_{const} \times \frac{\rho_m(\theta_i) \cos\theta_i}{z^2}$$

- 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”:

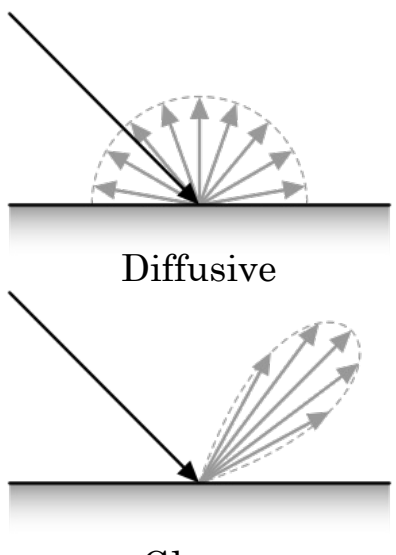
$$\mathcal{F}_m(\theta_i) = C_{const} \rho_m(\theta_i) \cos\theta_i$$

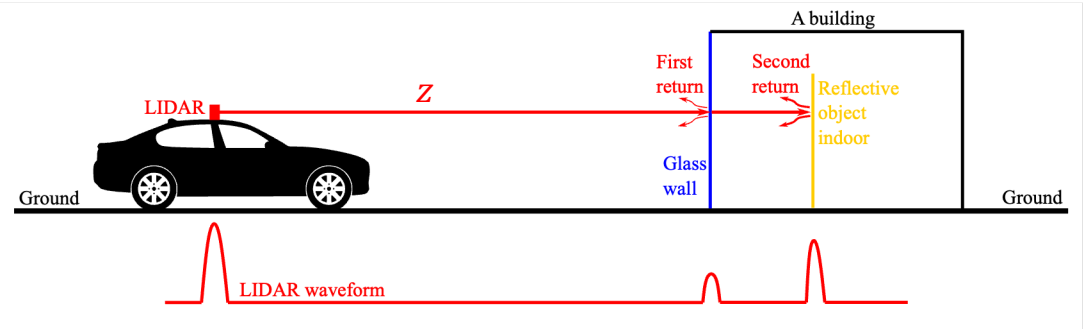
- It is obtained by decoupling LiDAR’s intensity from distance z as:

$$\mathcal{F}_m(\theta_i) = I(m, z, \theta_i) \, z^2$$



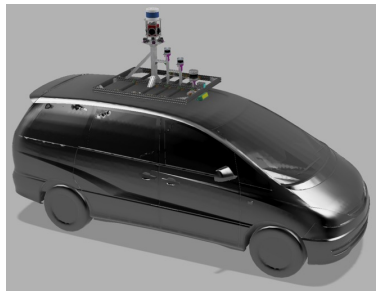
BRDF notations

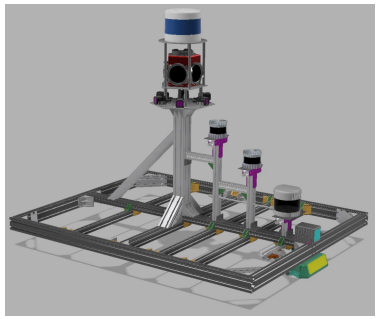




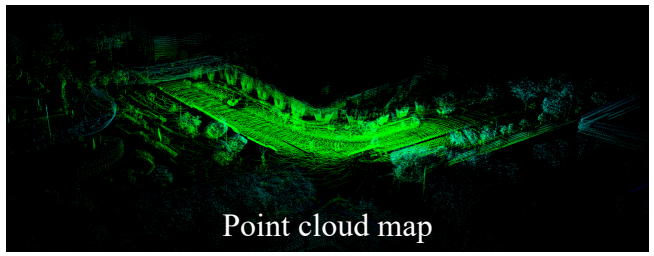
Transmission and remission of a LiDAR’s laser beam

Four objectives of my current research





Capture data

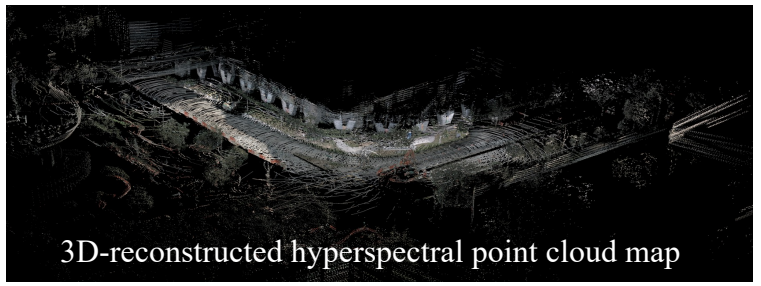


Point cloud map

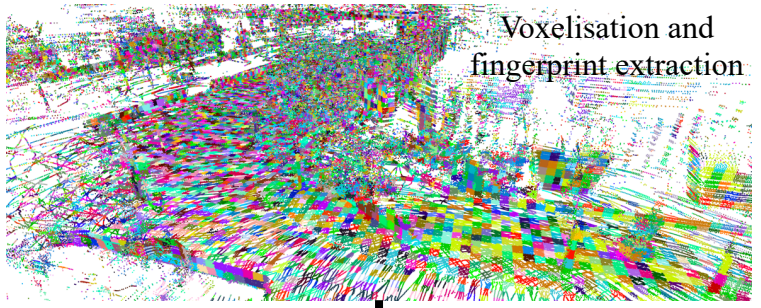
Visual and thermal images

Multispectral & multimodal perception data

Sensors fusion



3D-reconstructed hyperspectral point cloud map

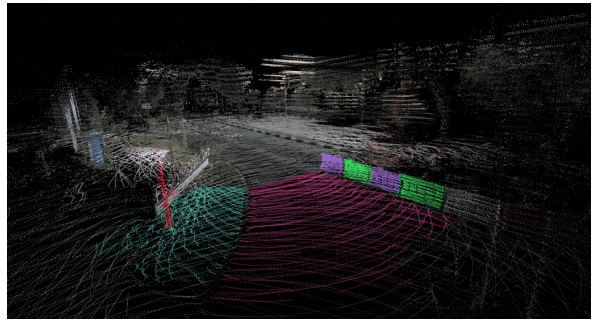


Voxelisation and fingerprint extraction

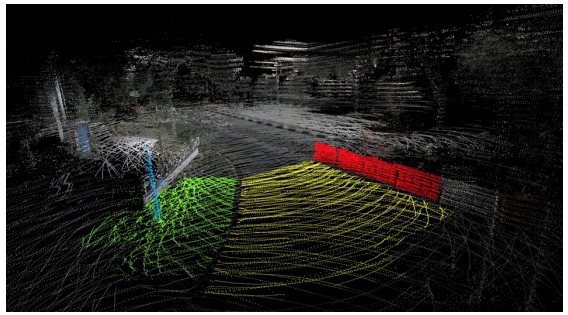
Material annotation

Perception dataset:
- Multispectral
- Multimodal
- With material segmentation

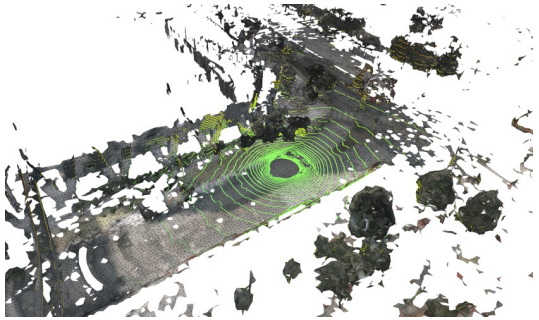
Material segmentation model



Material-segmented point cloud map



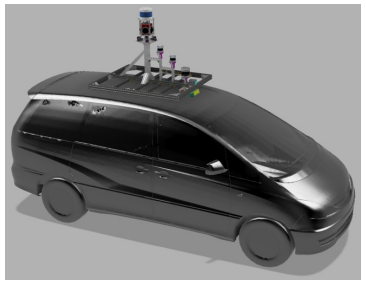
Novel semantic segmentation based on material

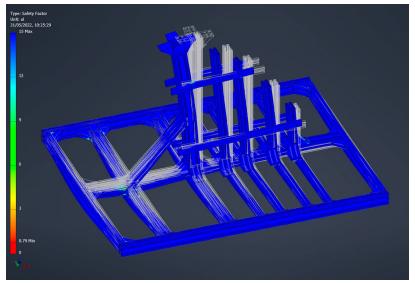


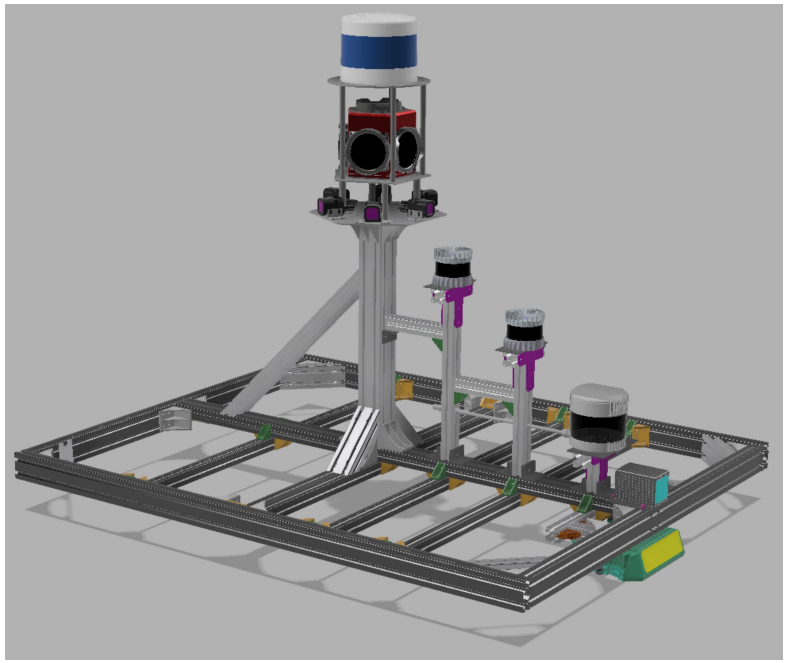
Hyperspectral & scalable digital twin

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

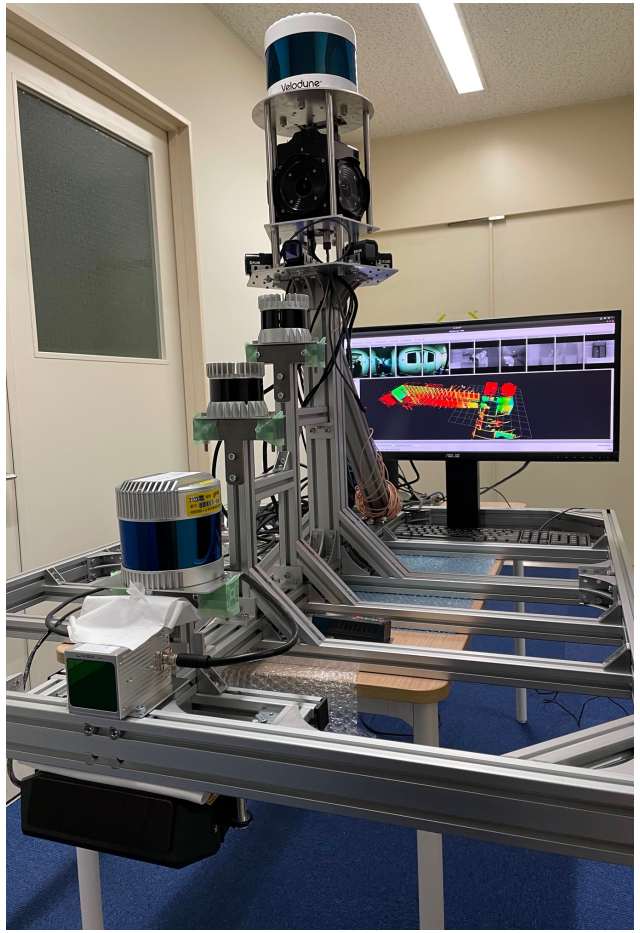
Engineering a multispectral & multimodal sensors system



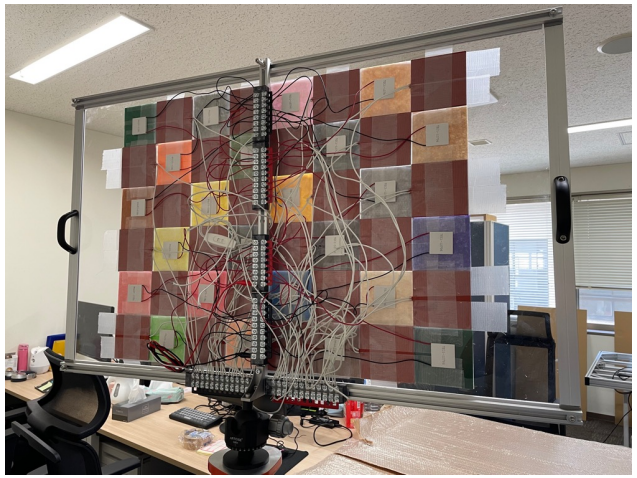




3D CAD and structural analysis

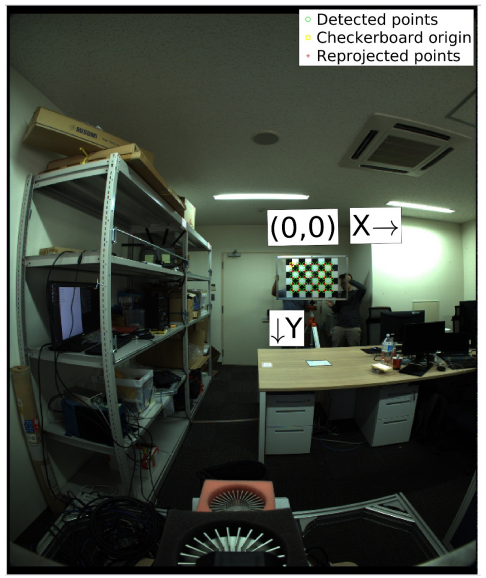


Assembly, ROS implementation, synchronisation

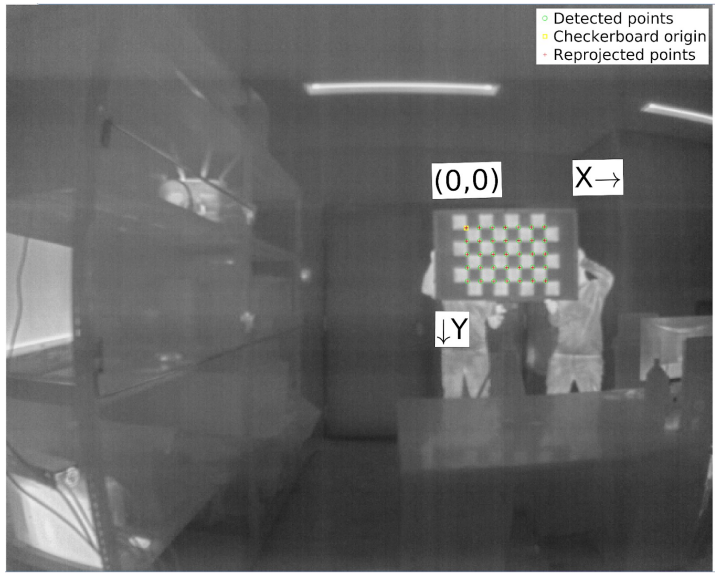


Calibration

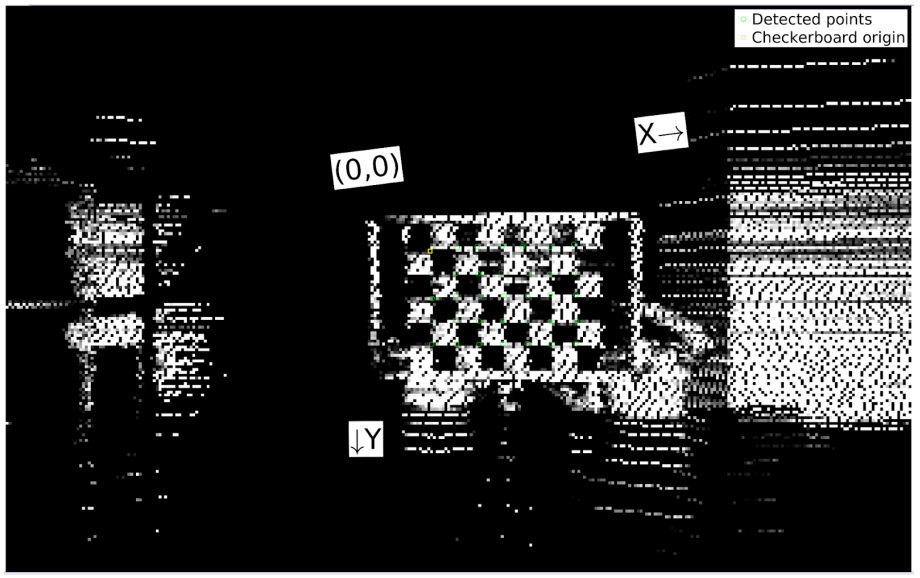
Joint calibration target for multiple sensor modalities



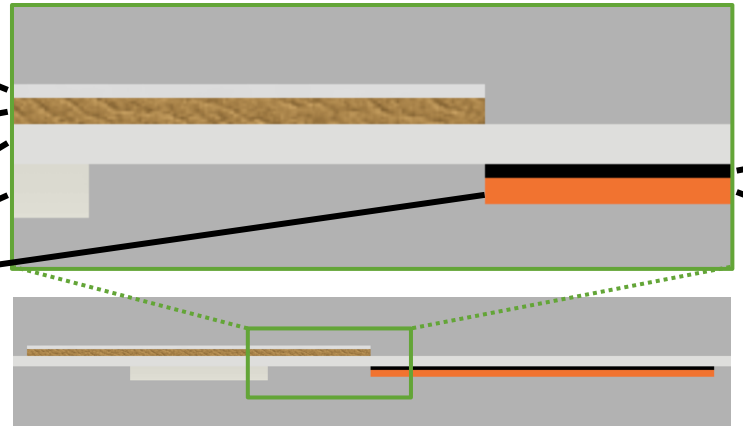
RGB image from Ladybug5



Thermal image from FLIR ADK camera



Point cloud snapshot from Velodyne VLS-128 AlphaPrime
(Black and white squares are made of aluminium and paper, which have distinct reflectivities)



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

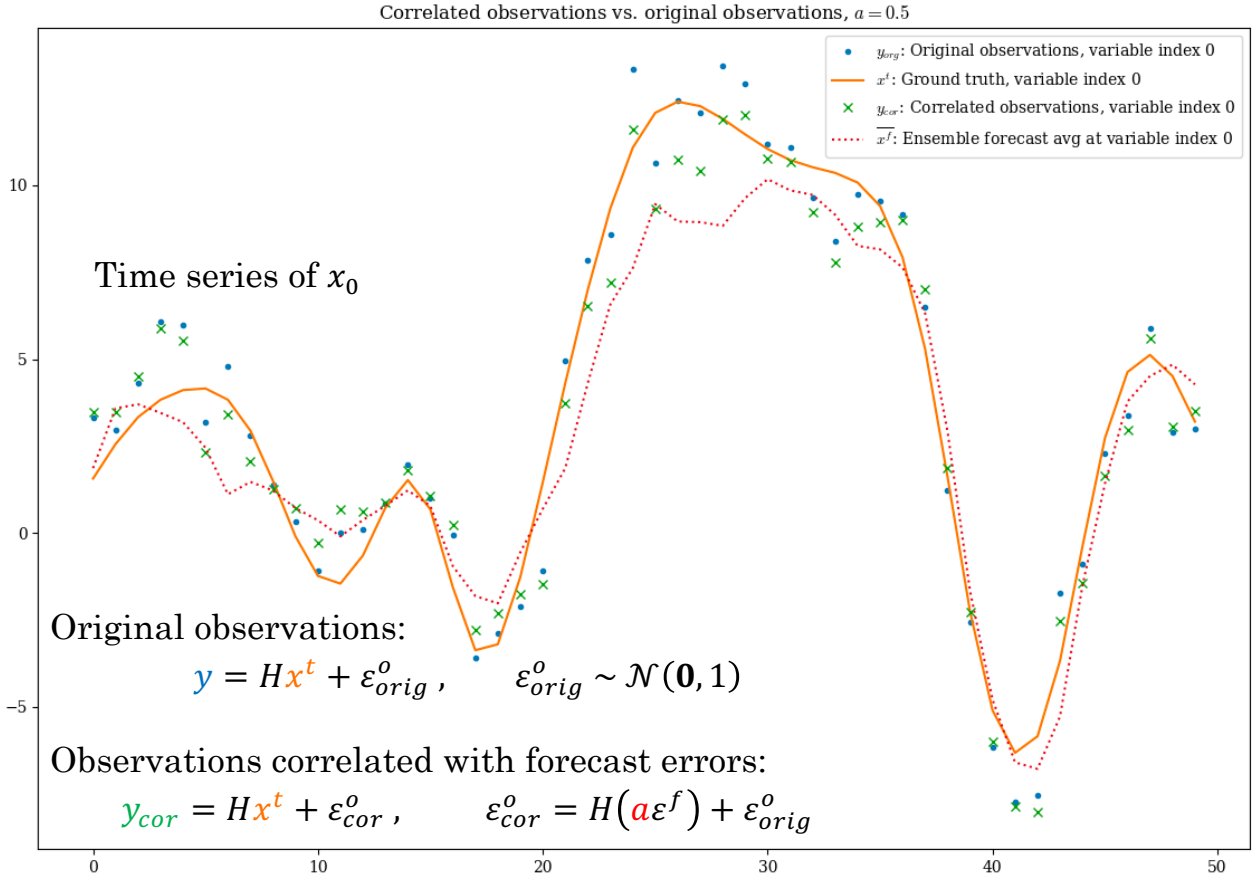
Data assimilation research at RIKEN CCS

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

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

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

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



- 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.