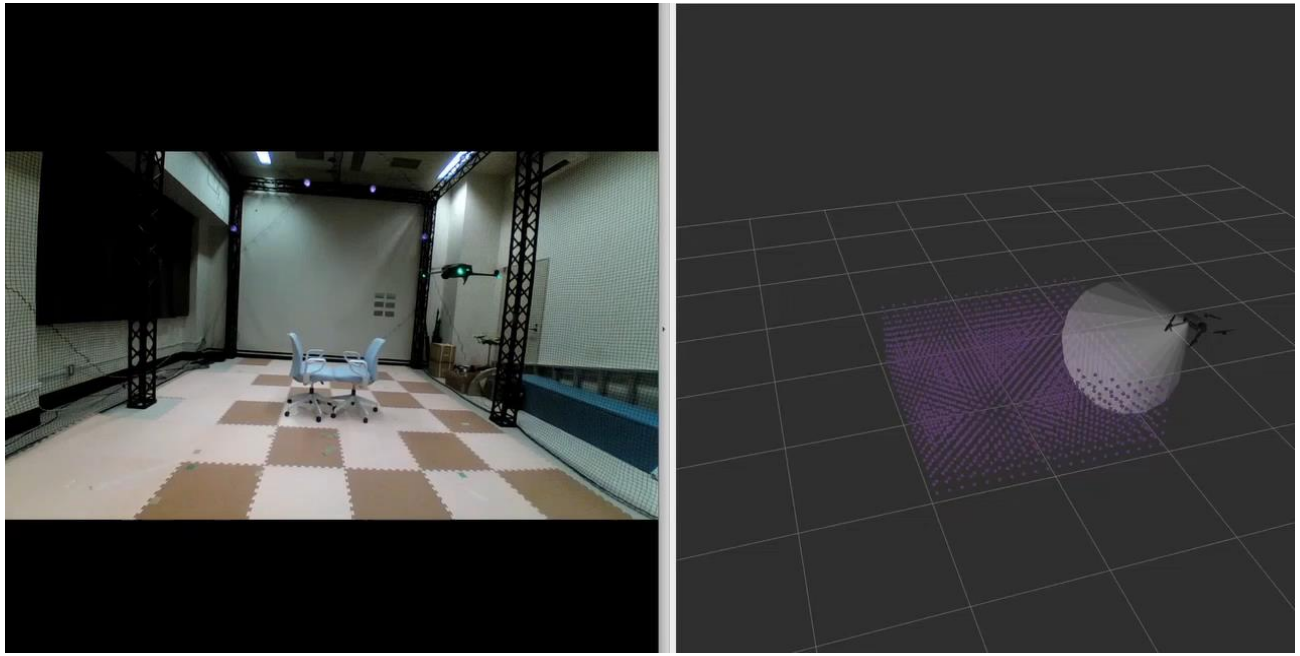
Visual 3D Model Reconstruction Technology Meets Coverage Control



Takeshi Hatanaka (Tokyo Tech)

University of Waterloo

July 5, 2024

Prologue: Agriculture 4.0 and Multi-robot Coordination

DLG, Digitalisierung in der Landwirtschaft, DLG-Merkblatt 447 (2019)

https://www.dlg.org/de/landwirtschaft/themen/technik/digitalisierungarbeitswirtschaft-und-prozesstechnik/dlg-merkblatt-447

2.4 Automation und Robotik (Automation and Robotics)

It is already becoming apparent that autonomous <u>robots will mostly be small in size and electrically driven</u>. This will lead to considerable <u>reductions in investment costs and vehicle weights</u>. The lower the acquisition and investment costs, the lower the area performance can be. This effect helps with the acceptance of autonomous agricultural robots, because many tasks that a robot has to perform can be carried out much more precisely at low driving speeds, but above all with <u>less energy</u>. Such devices are lightweight and therefore <u>gentle on the soil</u>.

Scaling up to larger areas is NOT achieved by larger and faster machines, but via a swarm of similar and small robots cooperating with each other.

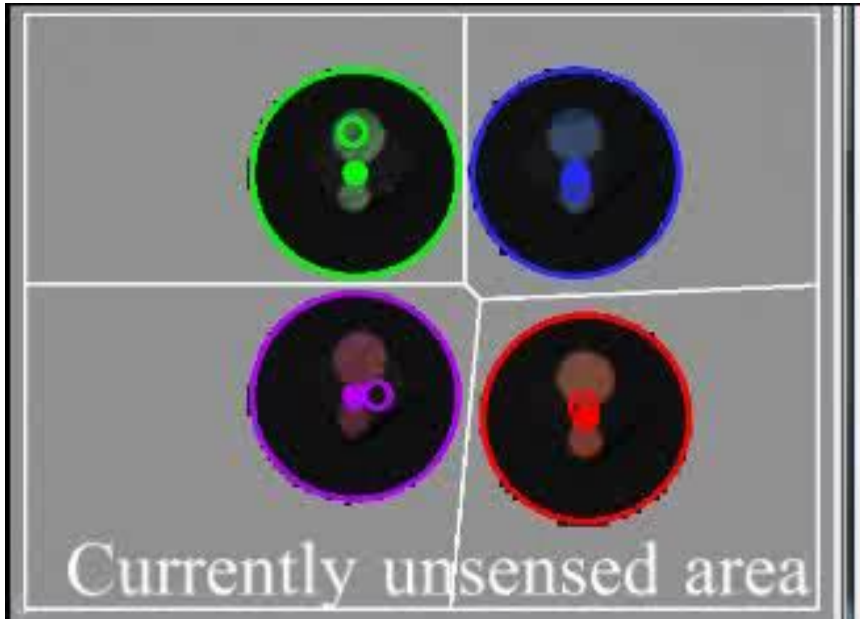
Persistent Coverage Control

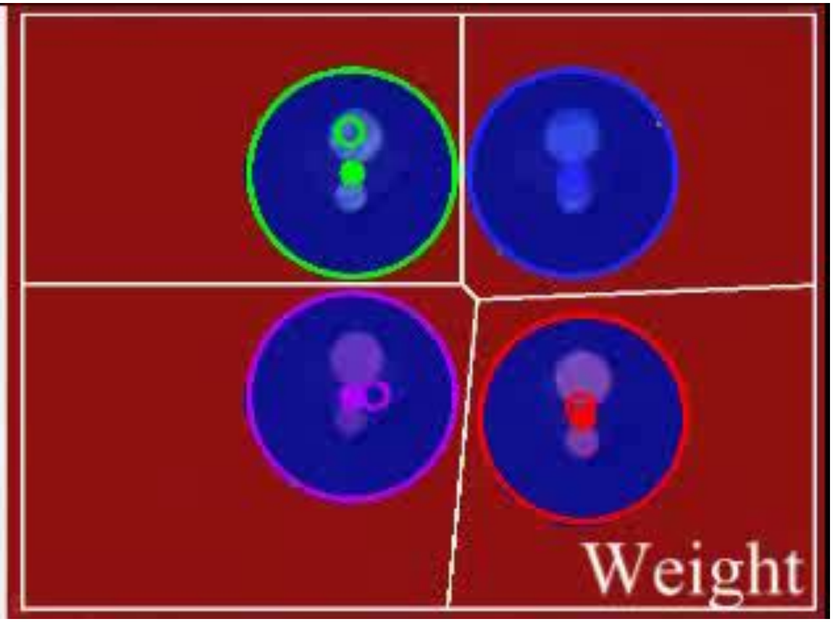
Density update

- $\dot{\phi}(q) < 0$ if q is monitored by a robot
- $\dot{\phi}(q) > 0$ if q is not monitored by any robot

e.g.

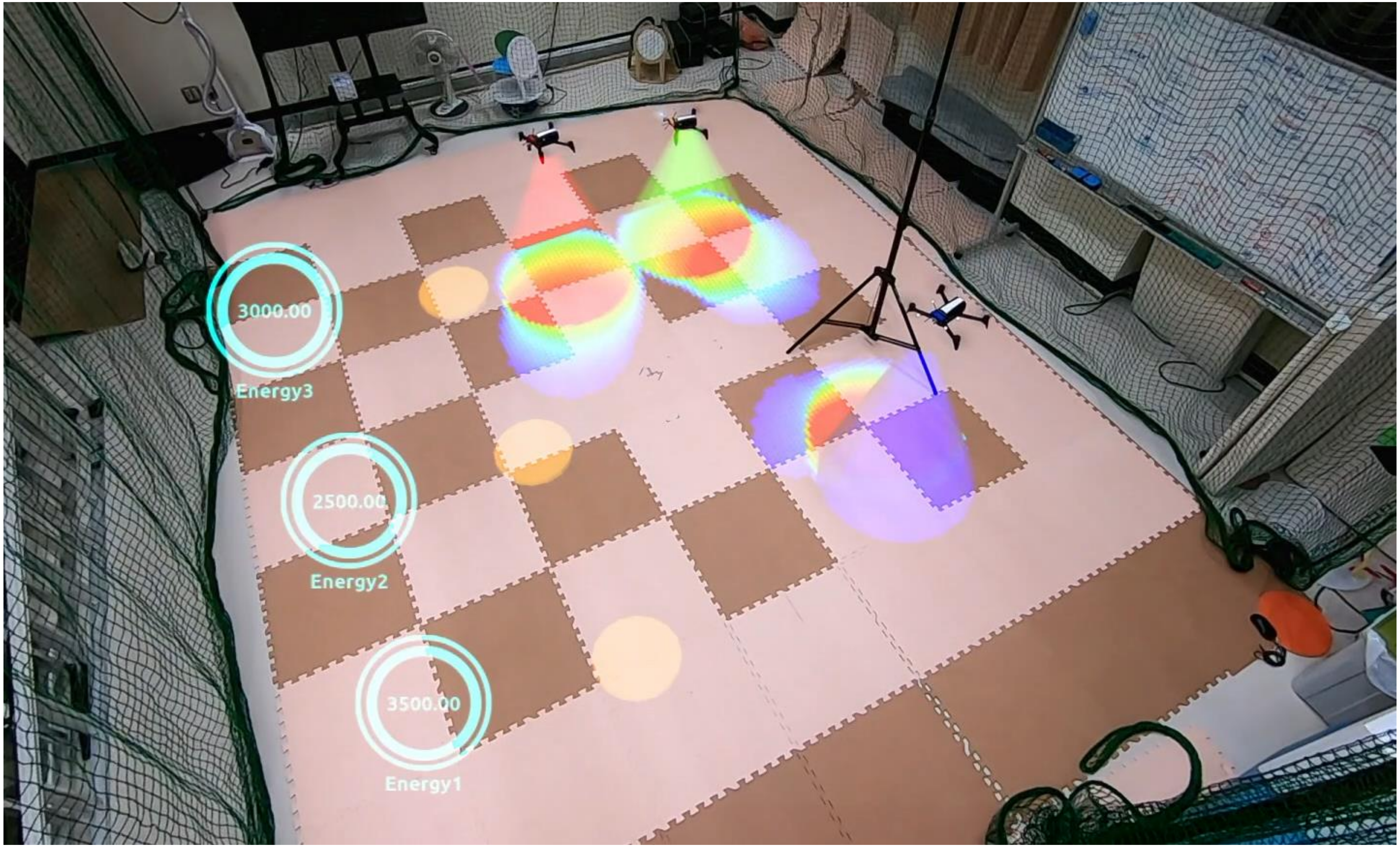
$$\dot{\phi}(q) = \begin{cases} -\delta\phi(q), & \text{if } q \text{ is monitored} \\ \delta(1-\phi(q)), & \text{otherwise} \end{cases}$$



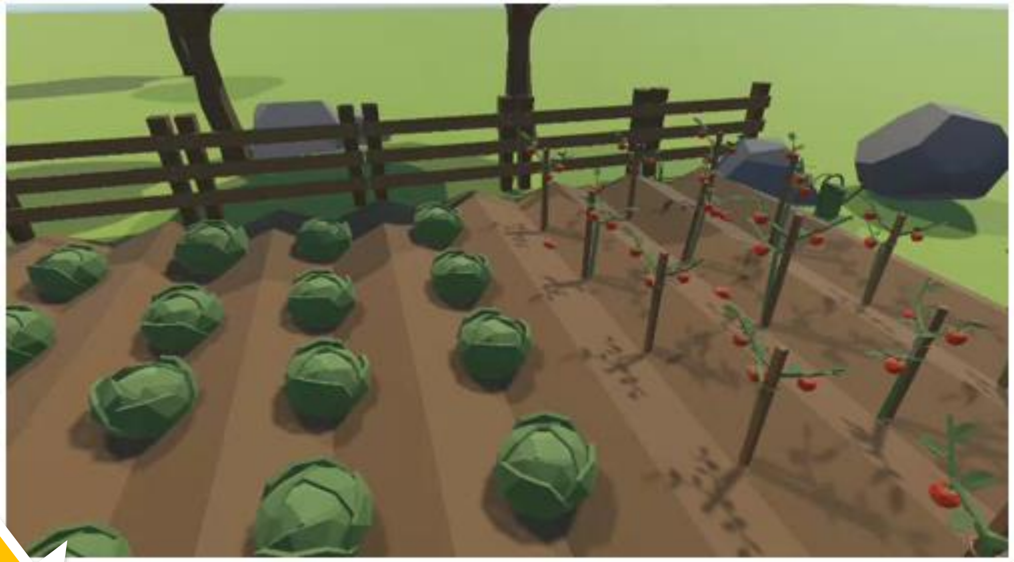


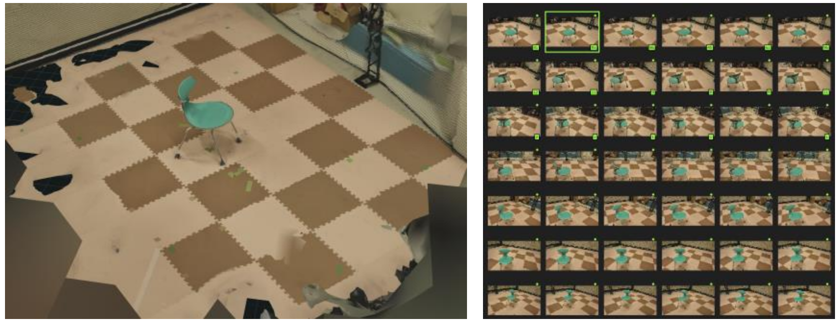
N. Hubel, S. Hirche, A. Gusrialdi, T. Hatanaka, M. Fujita, and O. Sawodny, "Coverage Control with Information Decay in Dynamic Environments," in *Proceedings of IFAC WC*, pp. 4180–4185, 2008.

Persistent Coverage Control

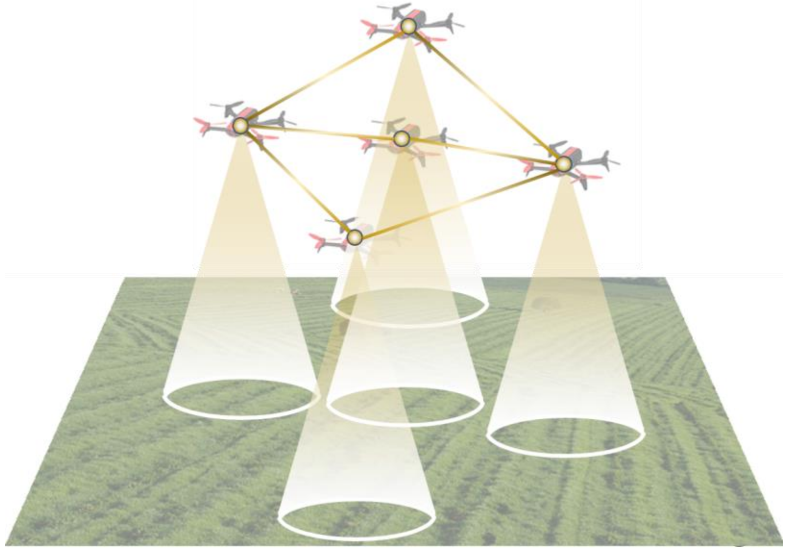


Coordinated Image Sampling for 3D Mapping



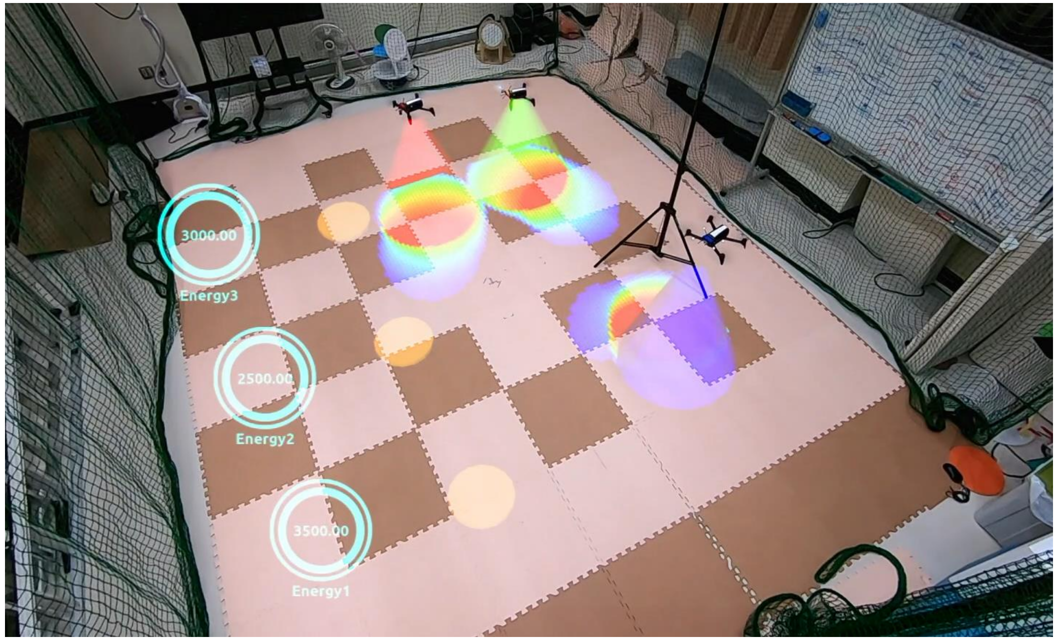


Structure from Motion (SfM)



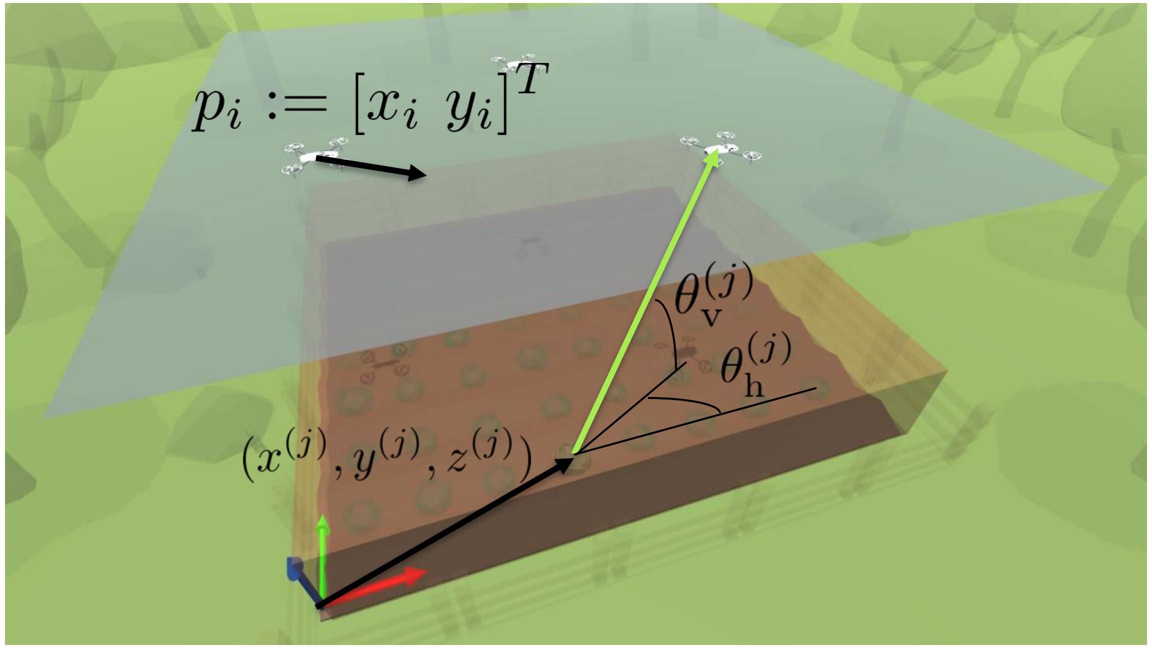
Persistent Coverage vs Image Sampling

capture within FOV (2D)



revisit many times

sample from various angles (5D)



sampling just once is enough

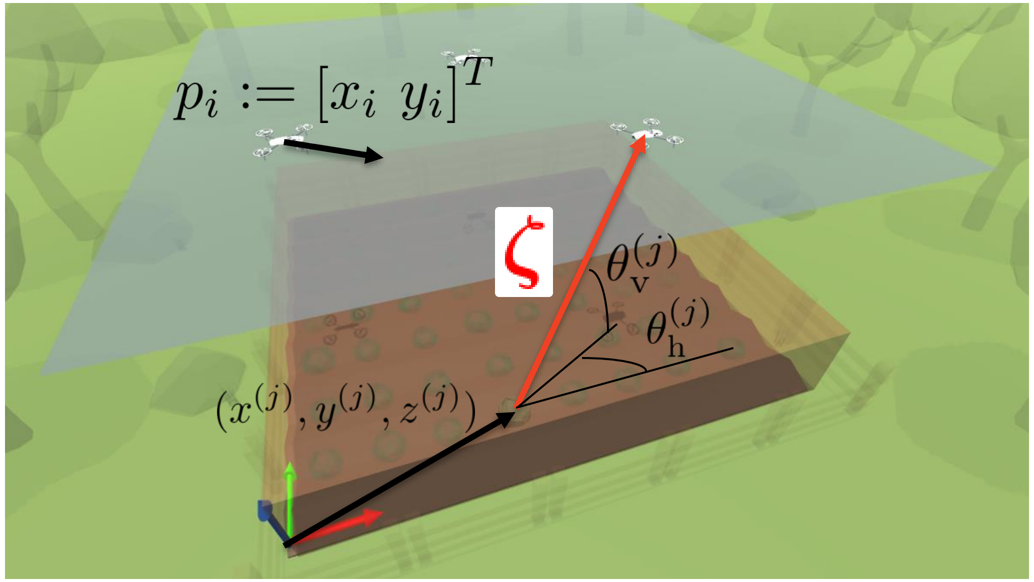
Problem Formulation

drone dynamics

$$\dot{p}_i = u_i$$

observation points

$$q_j \in \mathbb{R}^5 \quad (j = 1, 2, \ldots, m)$$



$$\zeta : [x \ y \ z \ \theta_{\mathrm{h}} \ \theta_{\mathrm{v}}]^T \mapsto \begin{bmatrix} x - (z_c - z)\tan\left(\frac{\pi}{2} - \theta_{\mathrm{v}}\right)\cos\theta_{\mathrm{h}} \\ y - (z_c - z)\tan\left(\frac{\pi}{2} - \theta_{\mathrm{v}}\right)\sin\theta_{\mathrm{h}} \end{bmatrix}$$

sensing performance

$$f(p_i, q) = \exp\left(-\frac{\|p_i - \zeta(q)\|^2}{2\sigma^2}\right)$$

density update

$$\dot{\phi}_j = -\delta \max_{i \in \mathcal{I}} f(p_i, q_j)\phi_j \ \ (\delta > 0)$$

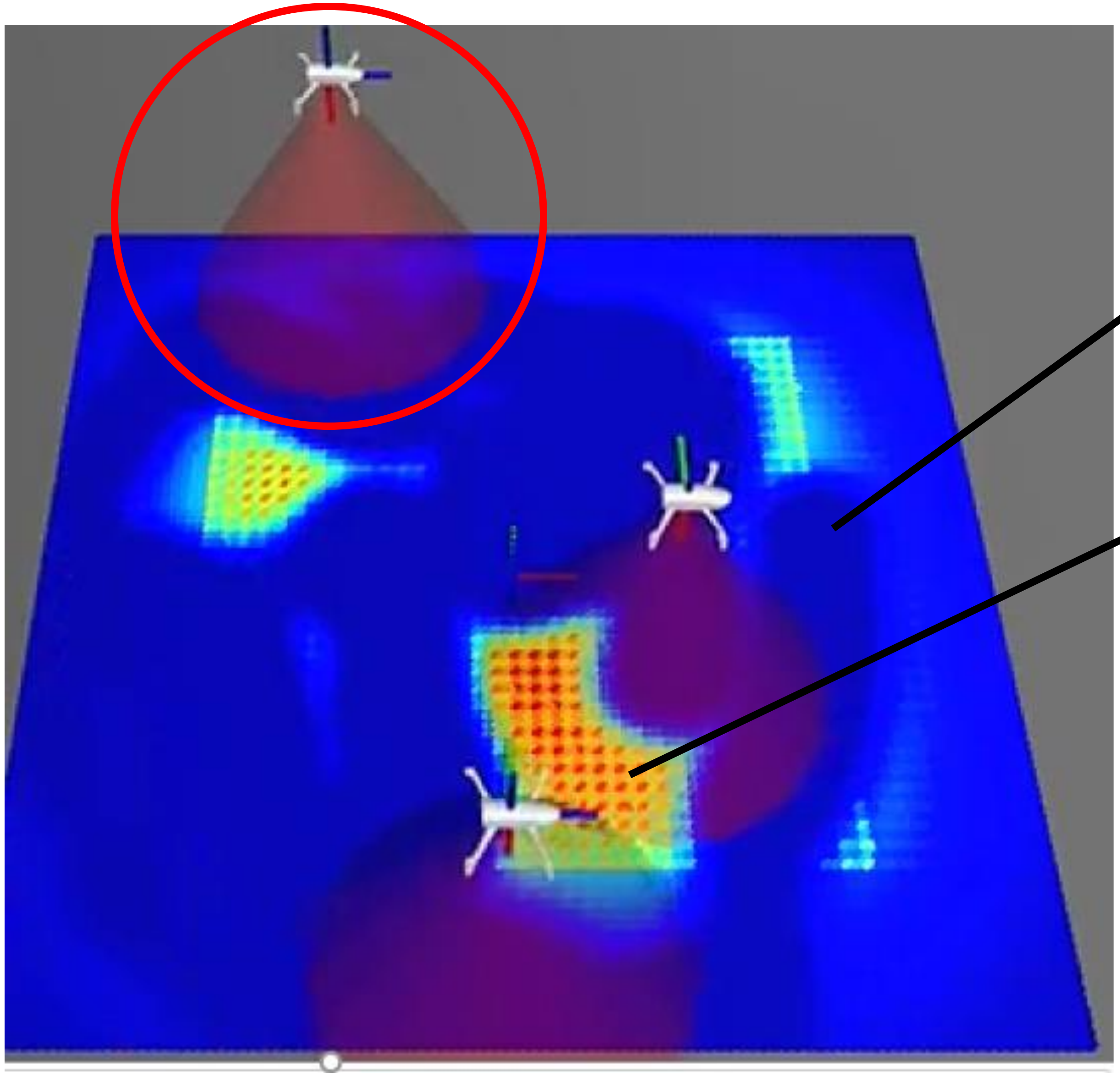
$$\dot{\phi}(q) = \begin{cases} -\delta\phi(q), & \text{if } q \text{ is monitored} \\ \delta(1 - \phi(q)), & \text{otherwise} \end{cases}$$

N. Hubel, S. Hirche, A. Gusrialdi, T. Hatanaka, M. Fujita, and O. Sawodny, "Coverage Control with Information Decay in Dynamic Environments," in *Proceedings of IFAC WC*, pp. 4180–4185, 2008.

objective function

$$J = \sum_{j=1}^{m} \phi_j$$

Difficulties in Gradient-based Method



well-observed area

unobserved area

Gradient-based method makes a drone be stuck to the well-observed area (opposite to the ideal motion)

Constraint-Based Coordinated Image Sampling

$$J = \sum_{j=1}^{m} \phi_j \to \min$$

Constraint-based specification

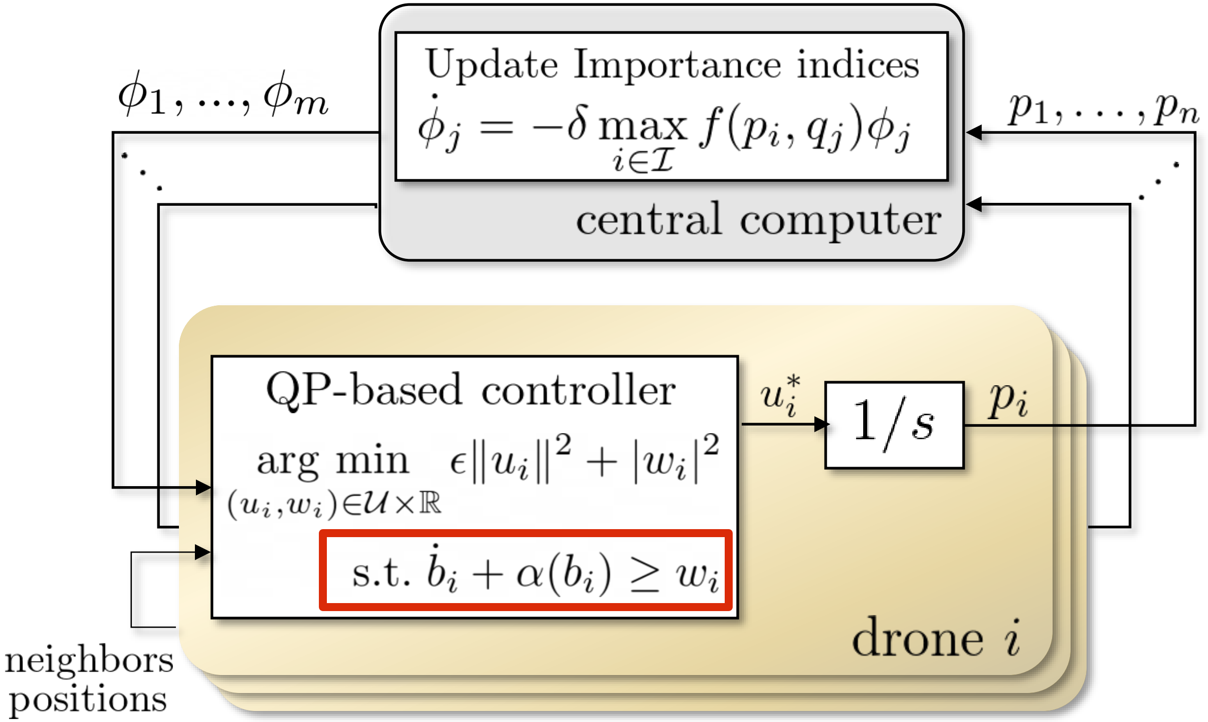
$$\dot{J} \leq -\gamma \Leftrightarrow b = -\dot{J} - \gamma \geq 0$$

$$\dot{J} = \sum_{j=1}^{m} \dot{\phi}_j = -\sum_{j=1}^{m} \delta \max_{i \in \mathcal{I}} f(p_i, q_j)\phi_j = -\sum_{i=1}^{n} \sum_{j \in \mathcal{V}_i(p)} \delta f(p_i, q_j)\phi_j = -\sum_{i=1}^{n} I_i$$

local constraint $-I_i \leq -\gamma/n$

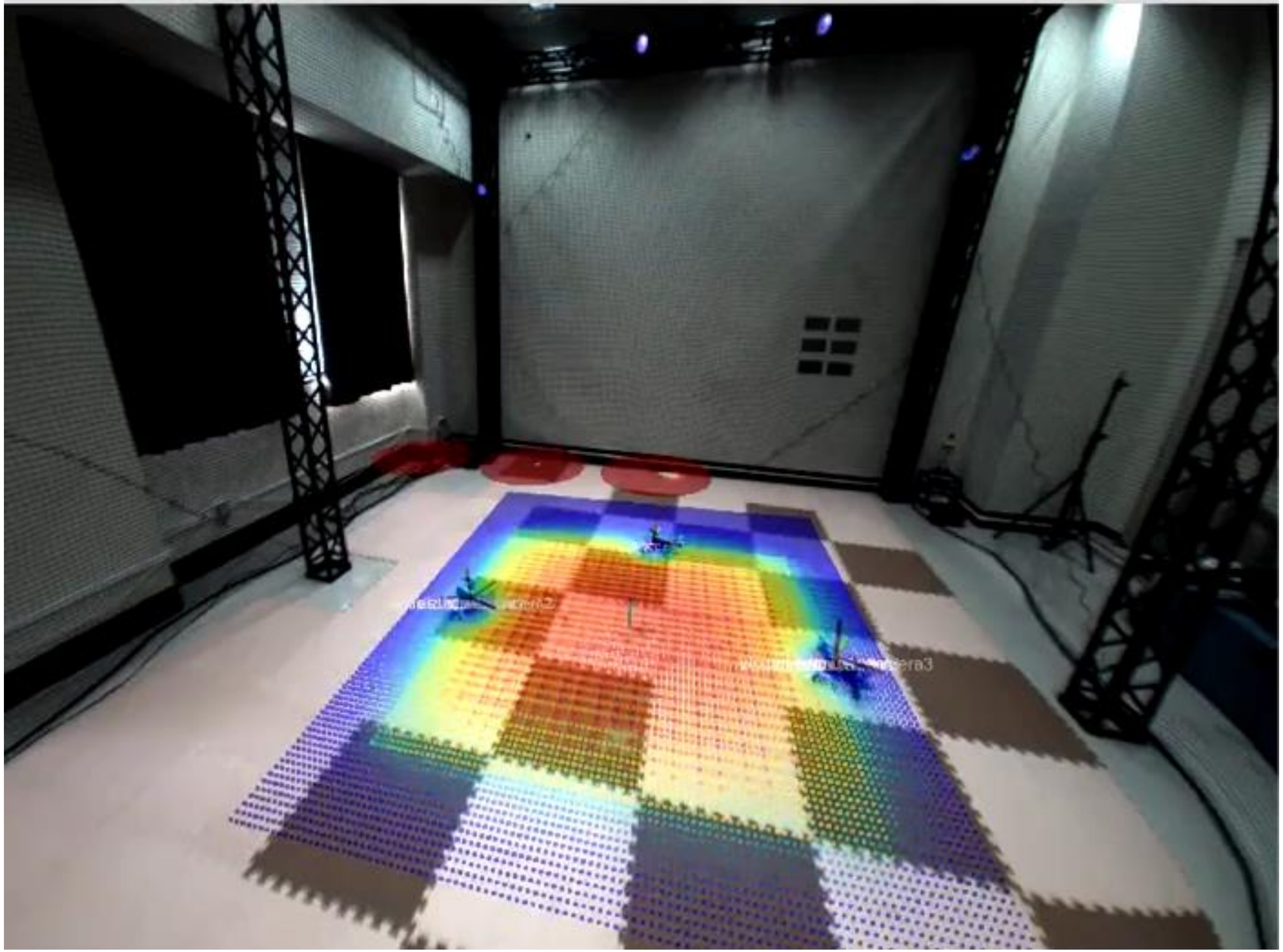
control barrier-like function

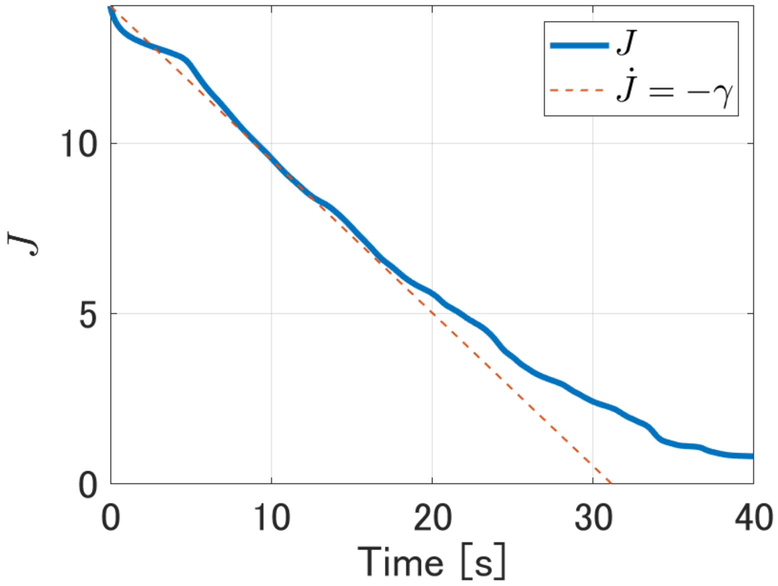
$$b_i = I_i - \gamma/n \geq 0$$

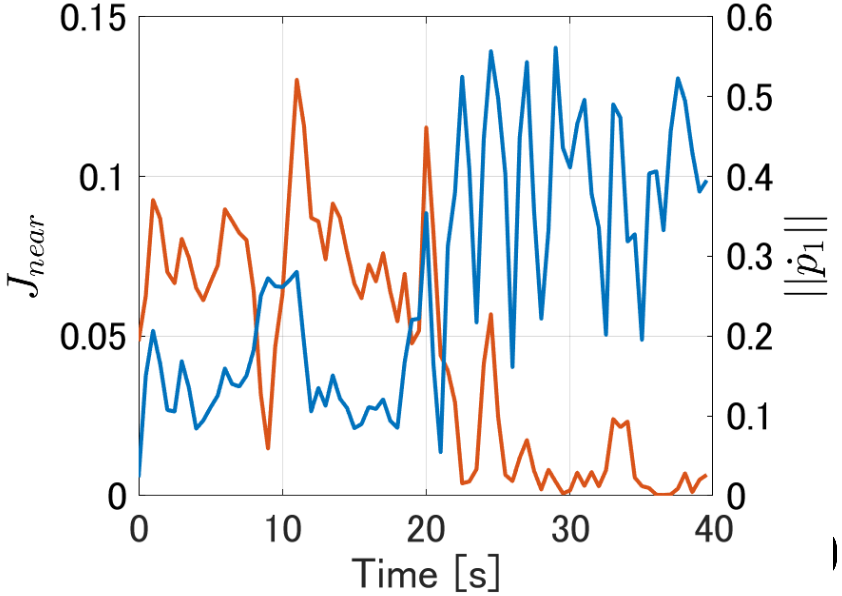


T. Shimizu, S. Yamashita, T. Hatanaka, K. Uto, M. Mammarella, and F. Dabbene, Angle-aware Coverage Control for 3D Map Reconstruction with Drone Networks, IEEE Control Systems Letters, vol. 6, pp. 1831-1836, 2022

Constraint-Based Coordinated Image Sampling

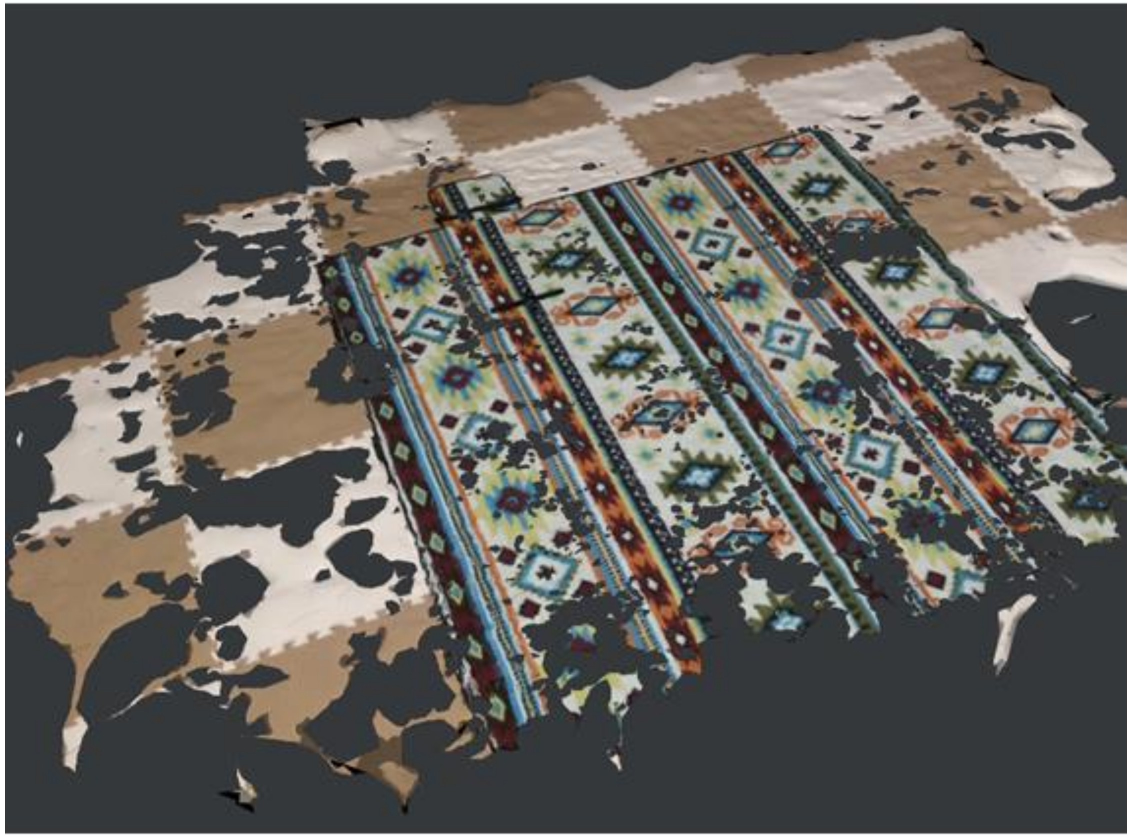






3D Model Reconstruction

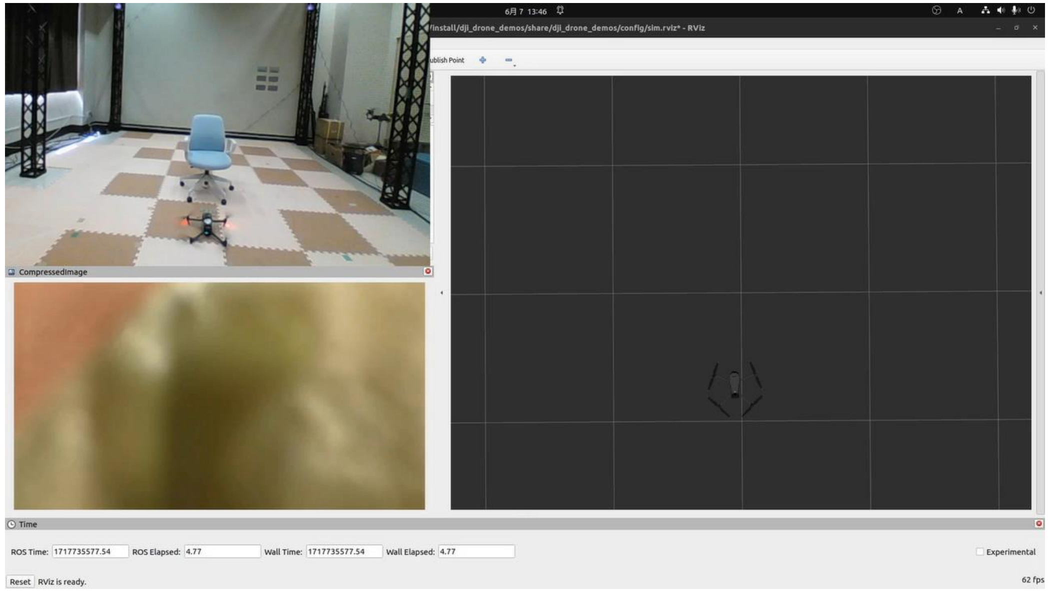
Conventional method

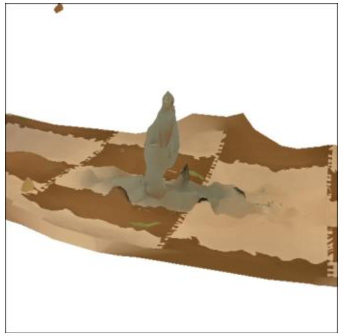


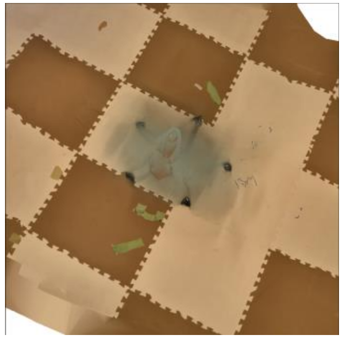
Angle-Aware method

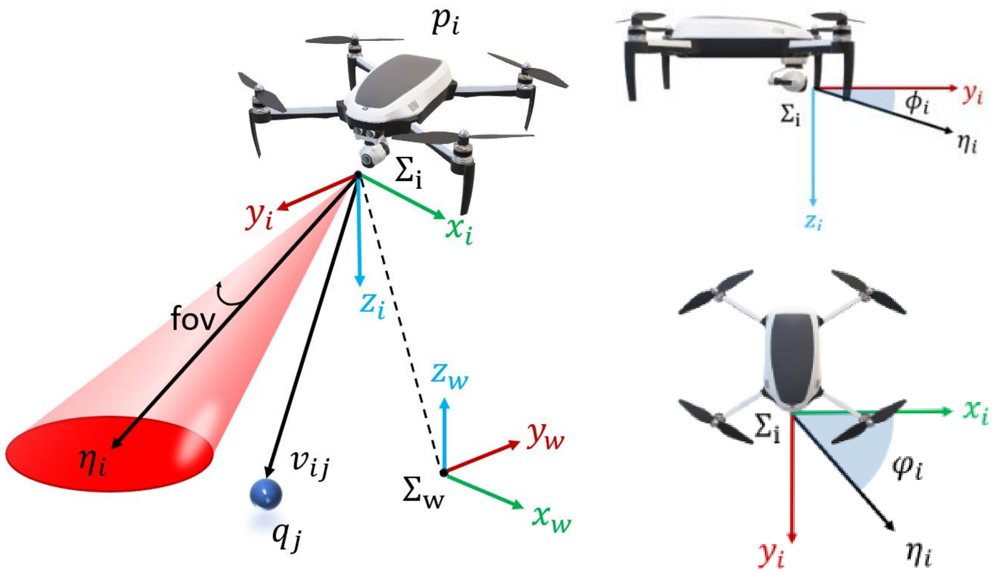
M. Suenaga, T. Shimizu, T. Hatanaka, K. Uto, M. Mammarella, and F. Dabbene, Experimental Study on Angle-aware Coverage Control with Application to 3-D Visual Map Reconstruction Proc. 2022 IEEE CCTA, pp. 327-333, 2022

3D Reconstruction with Objects









drone dynamics

$$\dot{p}_i = u_i \quad \dot{\phi}_i = u_i^{\phi} \quad \dot{\varphi}_i = u_i^{\varphi}$$

sensing performance

$$f(p_i, q_j) = \exp\left(-\frac{f_1(p_i, q_j)}{2\sigma_1^2}\right) \exp\left(-\frac{f_2(p_i, q_j)}{2\sigma_2^2}\right)$$

$$f_1(p_i, q_j) = (\arccos(\eta_i^T v_{ij}/\|v_{ij}\|))^2$$

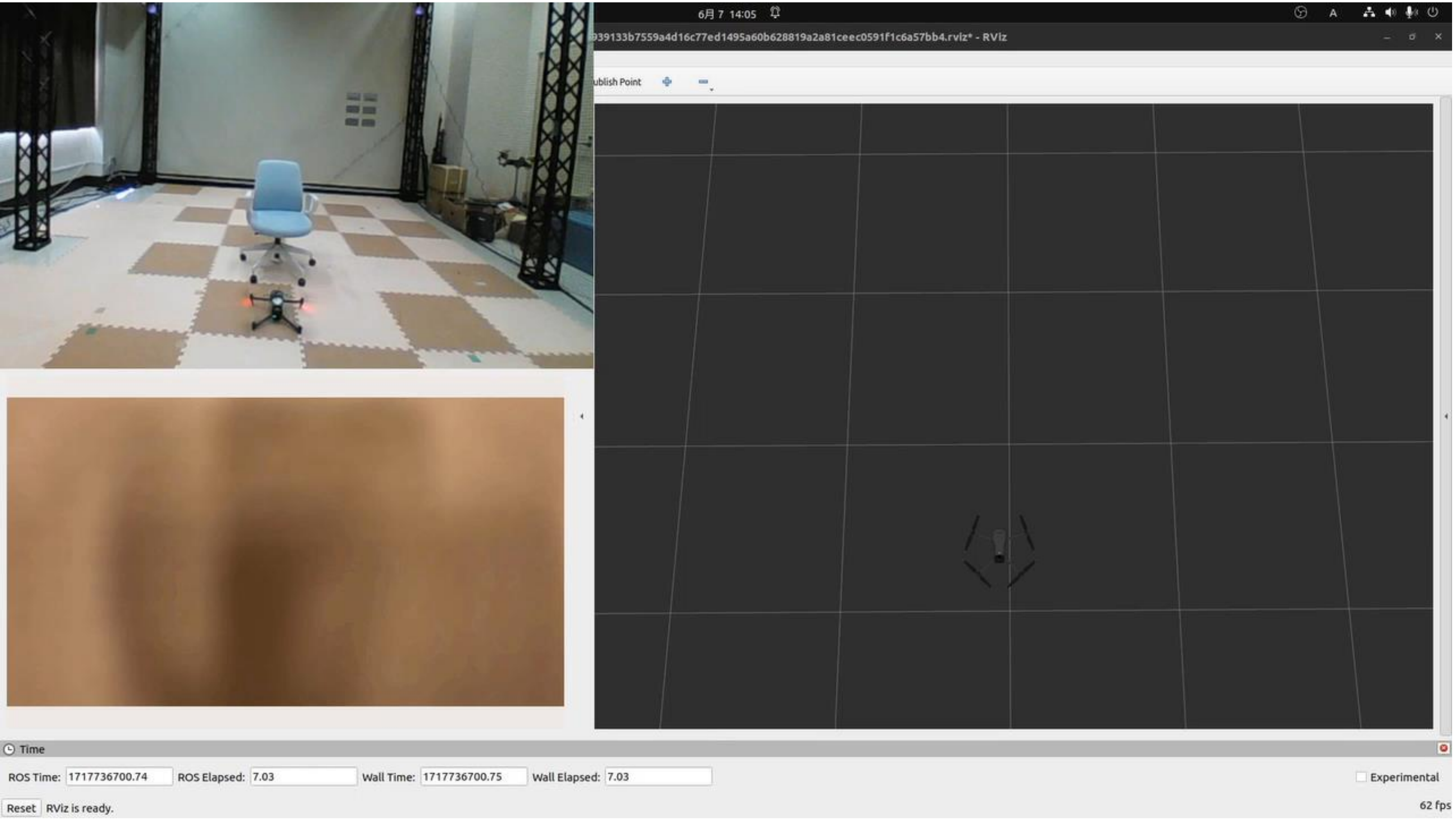
$$f_2(p_i, q_j) = (\arccos(v_j^T v_{ij}^w/\|v_{ij}^w\|))^2$$

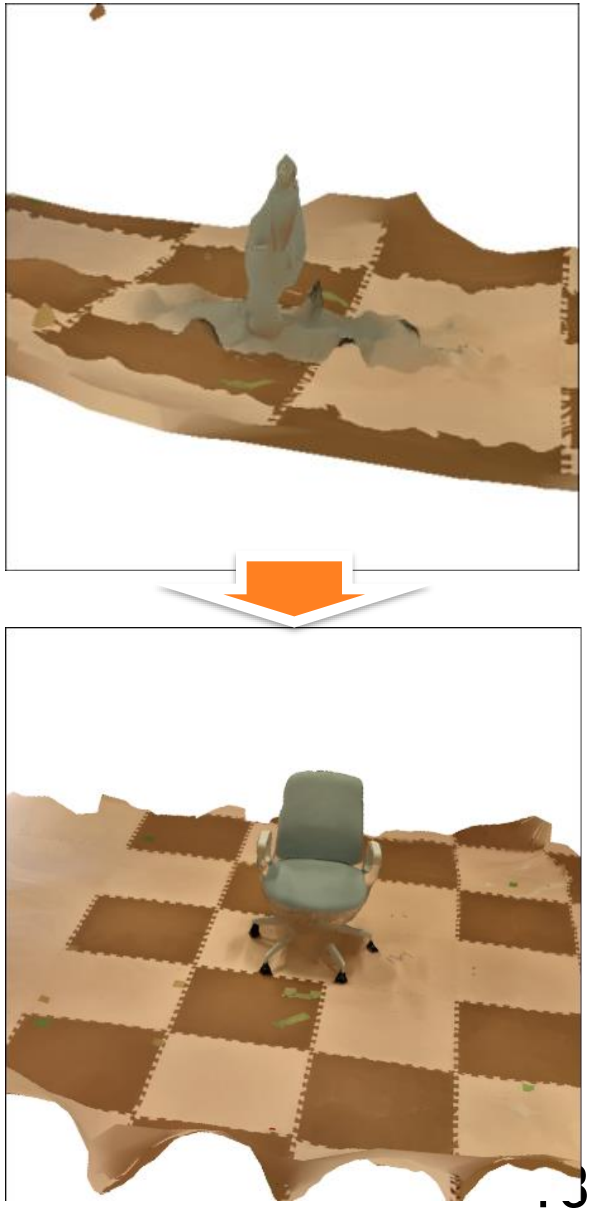
[ms]

	Central controller	Drone controller
CPU	212	1206
JIT, CPU	31	102
JIT, GPU	6	22

Z. Lu, M. Hanif, T. Shimizu, T. Hatanaka, Angle-aware Coverage with Camera Rotational Motion Control, SICE Journal of Control, Measurement, and System Integration, vol. 17, no. 1, pp. 211-221, 2024.

Angle-aware Coverage with Camera Rotation

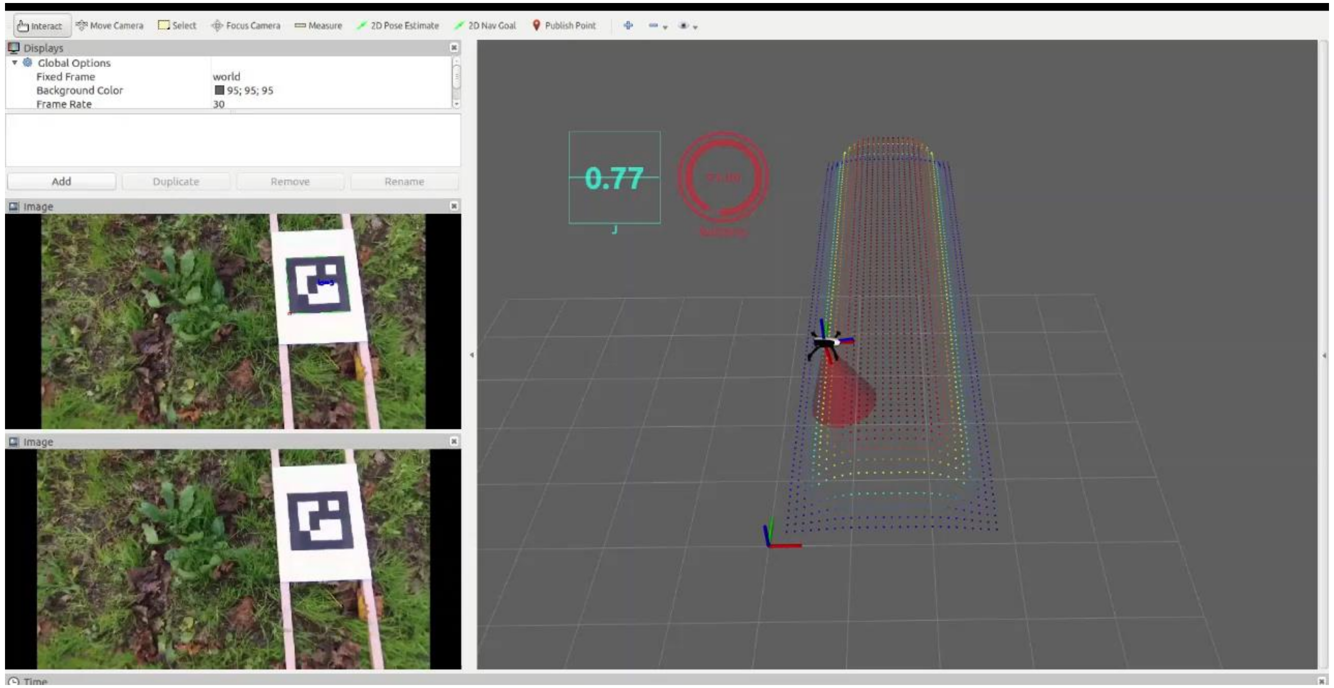




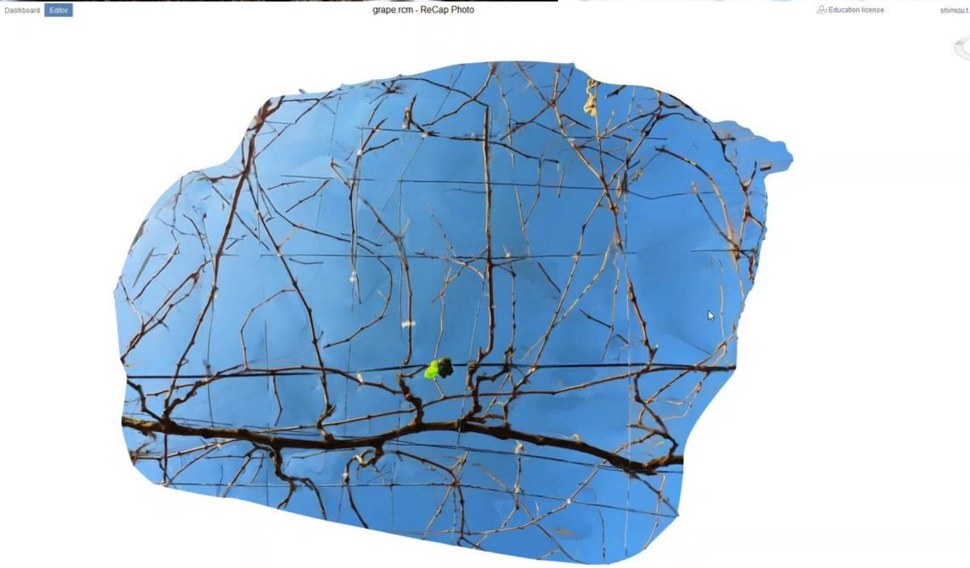
Z. Lu, M. Hanif, T. Shimizu, T. Hatanaka, Angle-aware Coverage with Camera Rotational Motion Control, SICE Journal of Control, Measurement, and System Integration, vol. 17, no. 1, pp. 211-221, 2024.

Field Experiment

Pear Orchard & Vineyard at Inagi City, Tokyo



Tokyo Tech



The use of AR markers prohibits us from experiments over wide area

New Experimental Field, Drone and System

Tokyo Tech

Smart Agriculture R&E Field

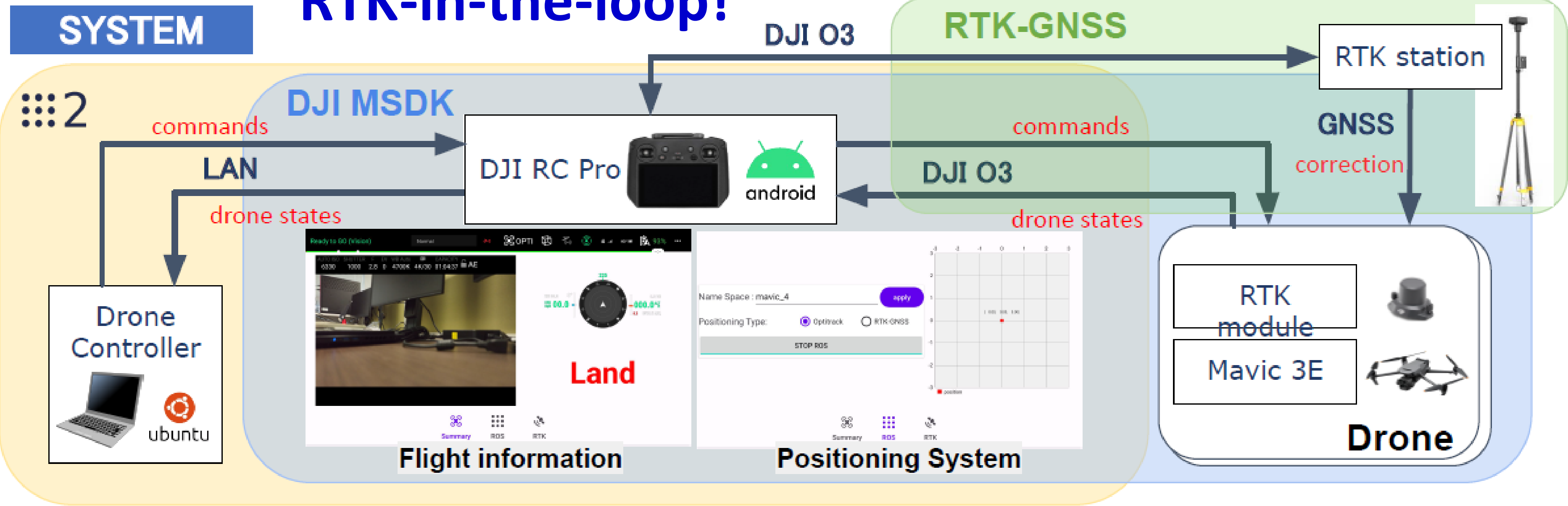


Tokyo Tech, Suzukakedai Campus

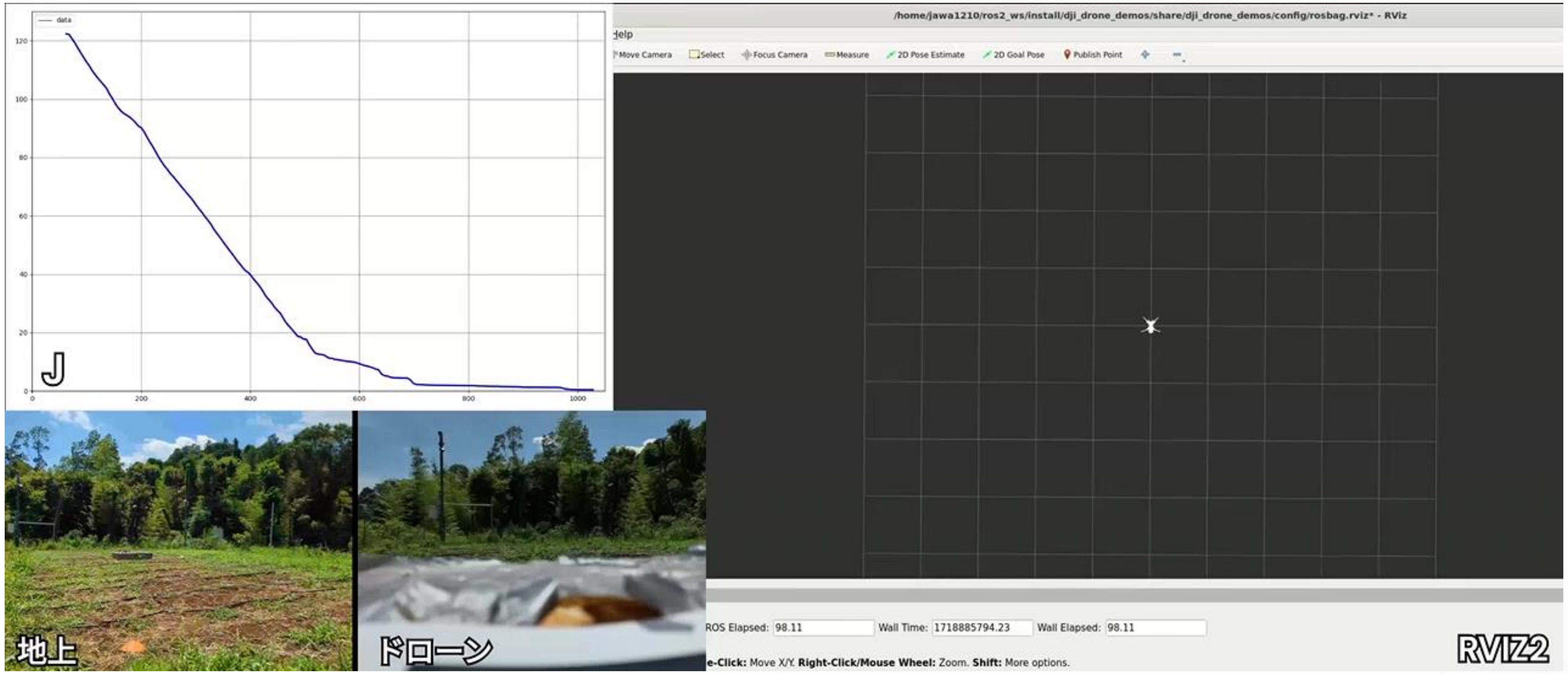

DJI Mavic 3E

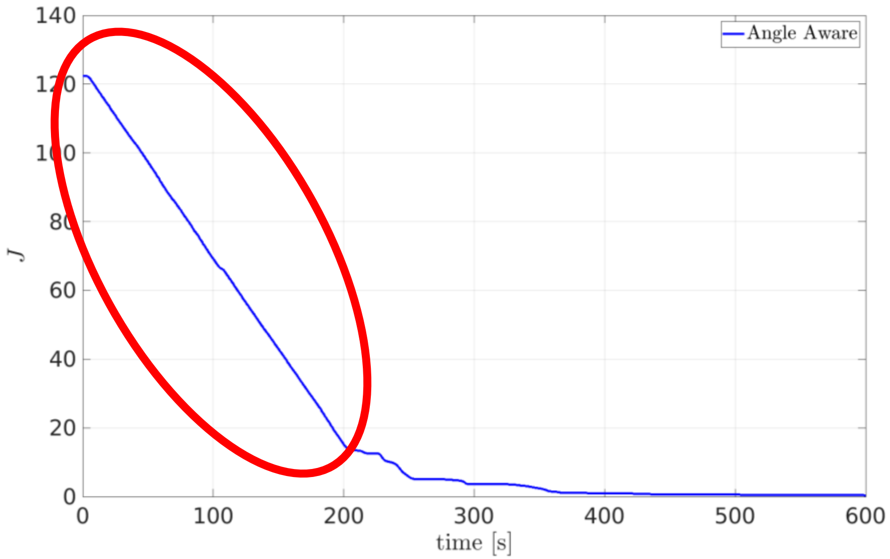
RTK module

RTK-in-the-loop!



New Experimental Field, Drone and System





The cable for ensuring safety prohibits multi-drone experiments …

(Near) Future Work

Tokyo Tech Academy for Super Smart Society
Tokyo Insutitute of Technology

Keisen University

We already had permissions from local governments and will start the multi-drone experiment in the end of this month

Model Predictive Coverage Scheduler

Geographical dispersal of small-scale farmlands

Decision variable

$$\delta_{ij} = \begin{cases} 1, & \text{if drone } i \text{ is assiged to field } j \\ 0, & \text{otherwise} \end{cases}$$

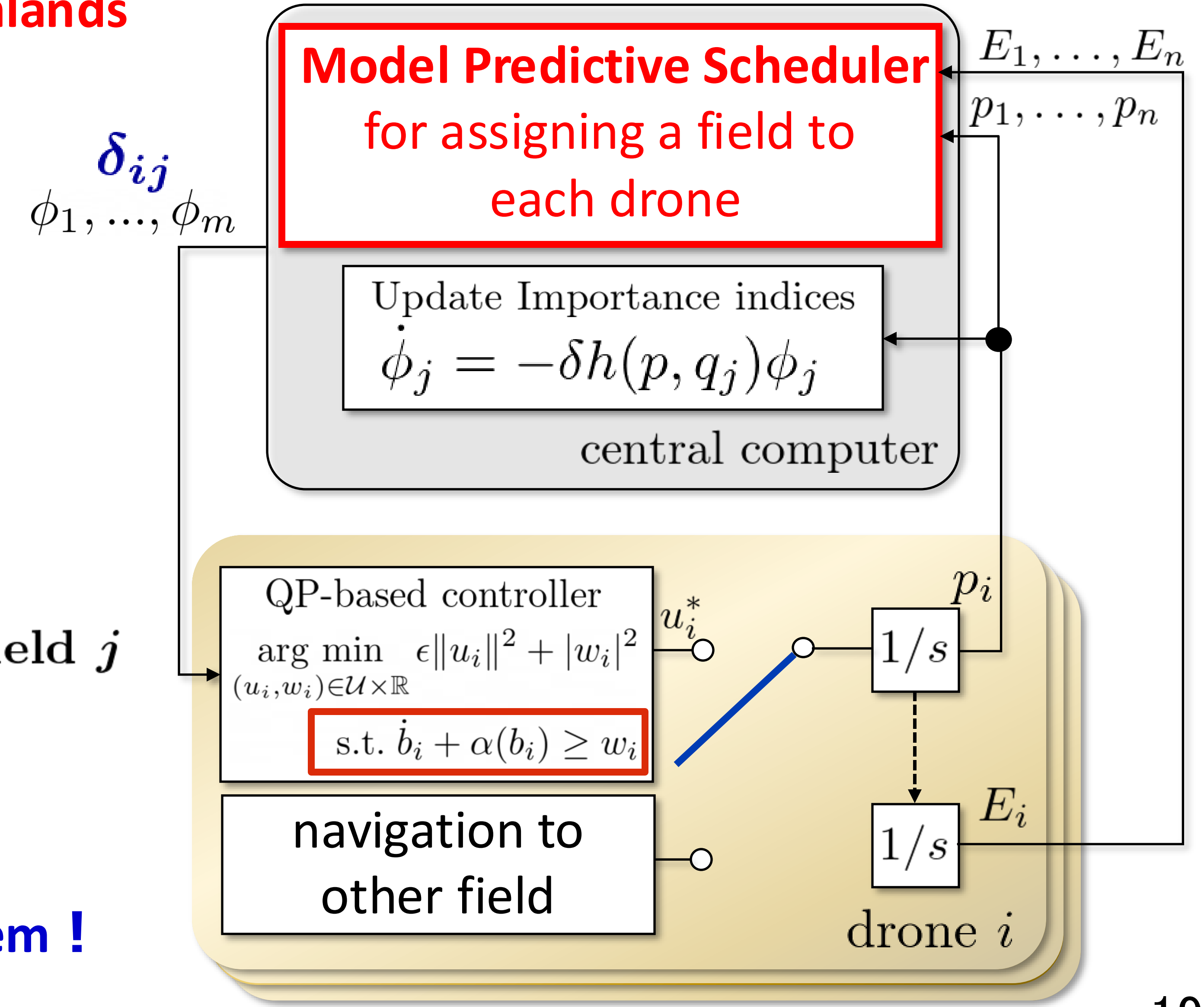
State equations

$$\dot{p}_i = u_i$$

$$\dot{E}_i = \begin{cases} -K_d, & \text{if } p_i \notin \mathcal{C} \\ K_c, & \text{if } p_i \in \mathcal{C} \end{cases}$$

Hybrid system！

$\mathcal{C}$ charging station



Model Predictive Coverage Scheduler

Geographical dispersal of small-scale farmlands

Goal: complete image sampling over all fields

$$J_j = A \sum_l \phi_{jl}, \quad \dot{\phi}_{jl} = -\delta f(p, q_{jl}) \phi_{jl}$$

Progress is quantified by the objective function value

Cost function: $\min \sum_j \|J_j\|^2$

Decision variable

$$\delta_{ij} = \begin{cases} 1, & \text{if drone } i \text{ is assiged to field } j \\ 0, & \text{otherwise} \end{cases}$$

State equations

$$\dot{p}_i = u_i$$

$$\dot{E}_i = \begin{cases} -K_d, & \text{if } p_i \notin \mathcal{C} \\ K_c, & \text{if } p_i \in \underline{\mathcal{C}} \end{cases}$$

Hybrid system !

charging station

Add ϕ_{jl} to state variables?

too many and highly nonlinear!

Model Predictive Coverage Scheduler

Cost Function: $\min \sum_j \|J_j\|^2$

Decision variable

$$\delta_{ij} = \begin{cases} 1, & \text{if drone } i \text{ is assiged to field } j \\ 0, & \text{otherwise} \end{cases}$$

State equations

$$\dot{p}_i = u_i$$

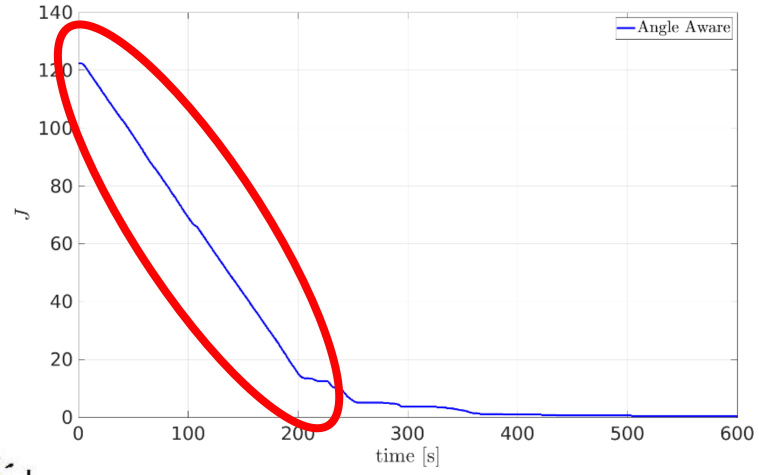
$$\dot{E}_i = \begin{cases} -K_d, & \text{if } p_i \notin \mathcal{C} \\ K_c, & \text{if } p_i \in \mathcal{C} \end{cases}$$

$$\dot{J}_j = \underline{-(\delta_{1j} + \cdots + \delta_{nj})\gamma}$$

linear time-invariant system

Adding various constraints such as $E_i \geq 0$ …

Constraint-based control $\dot{J} \leq -\gamma$



decays almost linearly!

CBF is useful for simplifying the control problem in a higher layer

D. Hijikata, M. Suenaga, Z. Lu, K. Uto, and T. Hatanaka, Hierarchical Coverage Scheduling and Control over Geographically Dispersed Farmlands with Multi-Drone Systems, Asian Journal of Control, submitted, 2024.

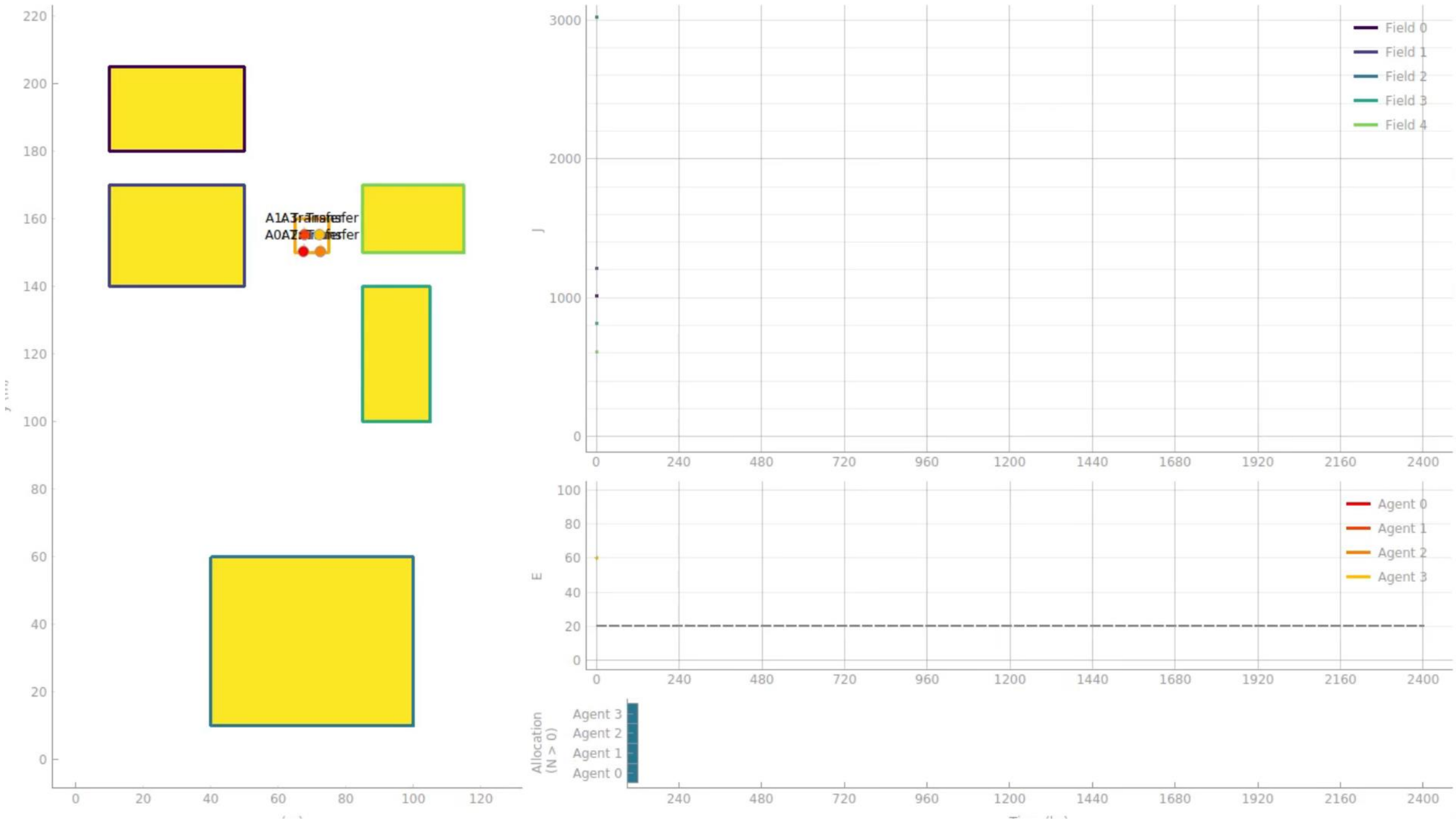
Simulation Setup

Tokyo Tech

Farmlands of my student

Item	Value	Unit	
dt	120	[s]	Sampling time and Gurobi calculation cycle
K1	100/3600	[-/s]	Battery consumption rate
K2	100/2700	[-/s]	Battery charge rate
gamma	4/15	[-]	Degree of decrease in importance function per one drone
E_max	100	[-]	Upper limit of battery
E_min	10	[-]	Lower limit of battery
u_max	10	[m/s]	Upper limit of speed input
u_min	-10	[m/s]	Lower limit of speed input
para_timelimit	30	[s]	Computation time upper limit per time step for Gurobi
para_gap	0.25	[%]	Tolerance to optimal solution of MIQP per time step for Gurobi
q	1	[-]	Coefficients of the weight matrix for importance function
r	1	[-]	Coefficients of the weight matrix for input

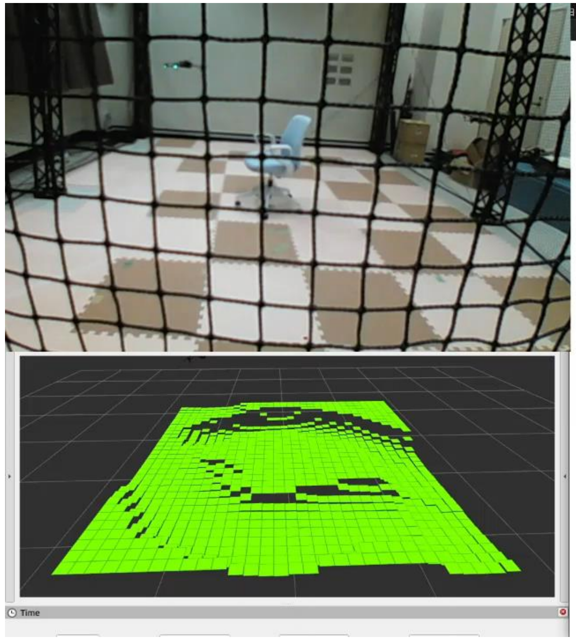
Simulation Result

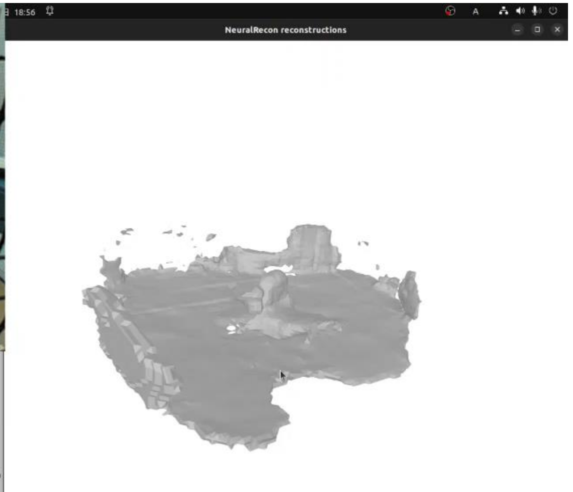


unpublished results

(for possible future collaborations)

Real-time Feedback of 3D Model



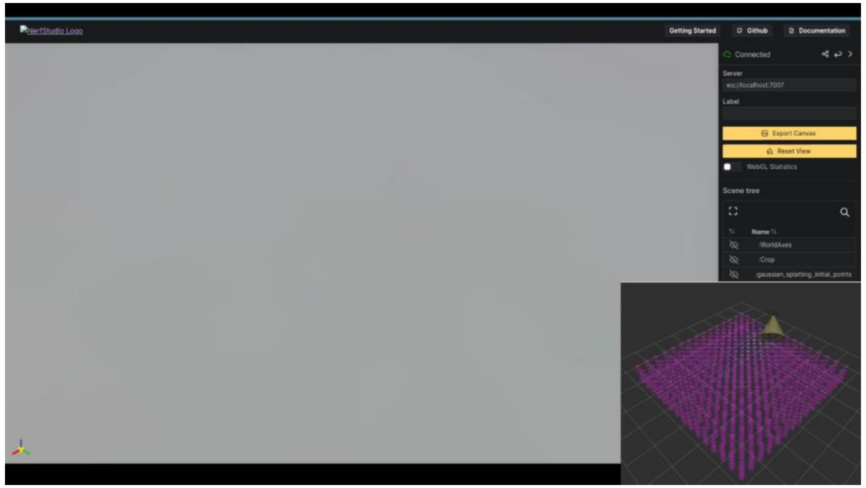


NeuralRecon(2021)

What can we do if 3D model is reconstructed in real time?

more advanced technologies will be available …

NeRF(2022)



Gaussian Splatting(2023)

Real-time Feedback of 3D Model

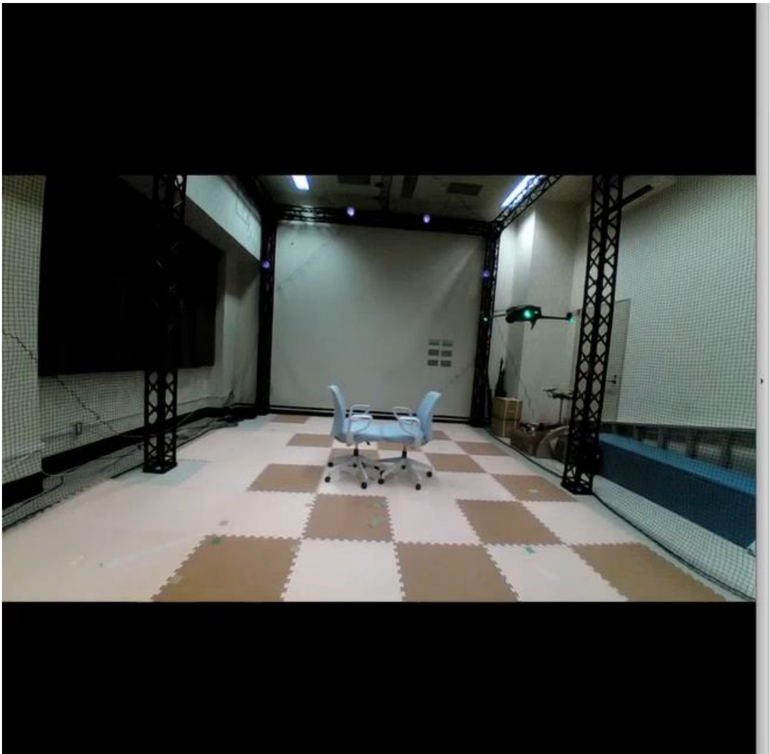
$$\dot{\phi}_j = -\delta \max_{i \in \mathcal{I}} f(p_i, q_j)\phi_j \ \ (\delta > 0)$$

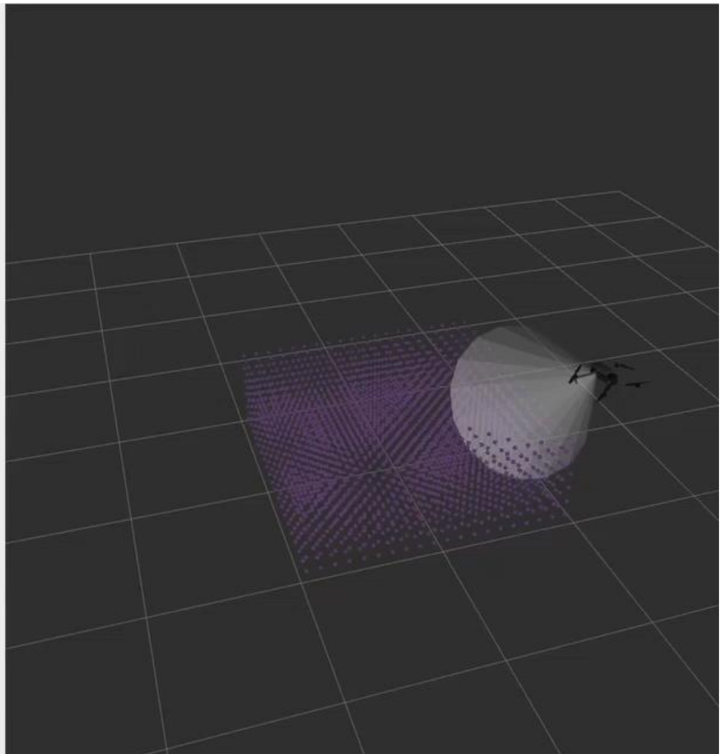
T. Shimizu, S. Yamashita, T. Hatanaka, K. Uto, M. Mammarella, and F. Dabbene, Angle-aware Coverage Control for 3D Map Reconstruction with Drone Networks, IEEE Control Systems Letters, vol. 6, pp. 1831-1836, 2022

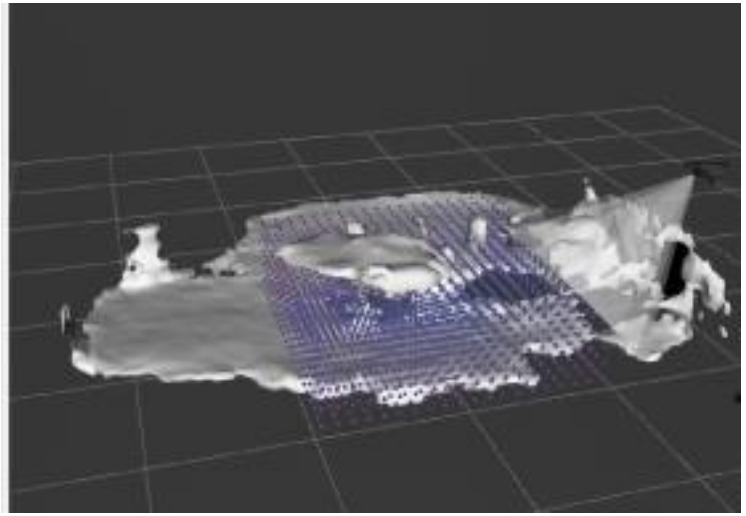
density update

$$\dot{\phi}_j = -\delta_1 \max_{i \in \mathcal{I}} f(p_i, q_j)\phi_j + \delta_2 \beta(\underline{\Delta \mathbf{mesh}_j})$$

quantify the size of mesh changes around j-th point

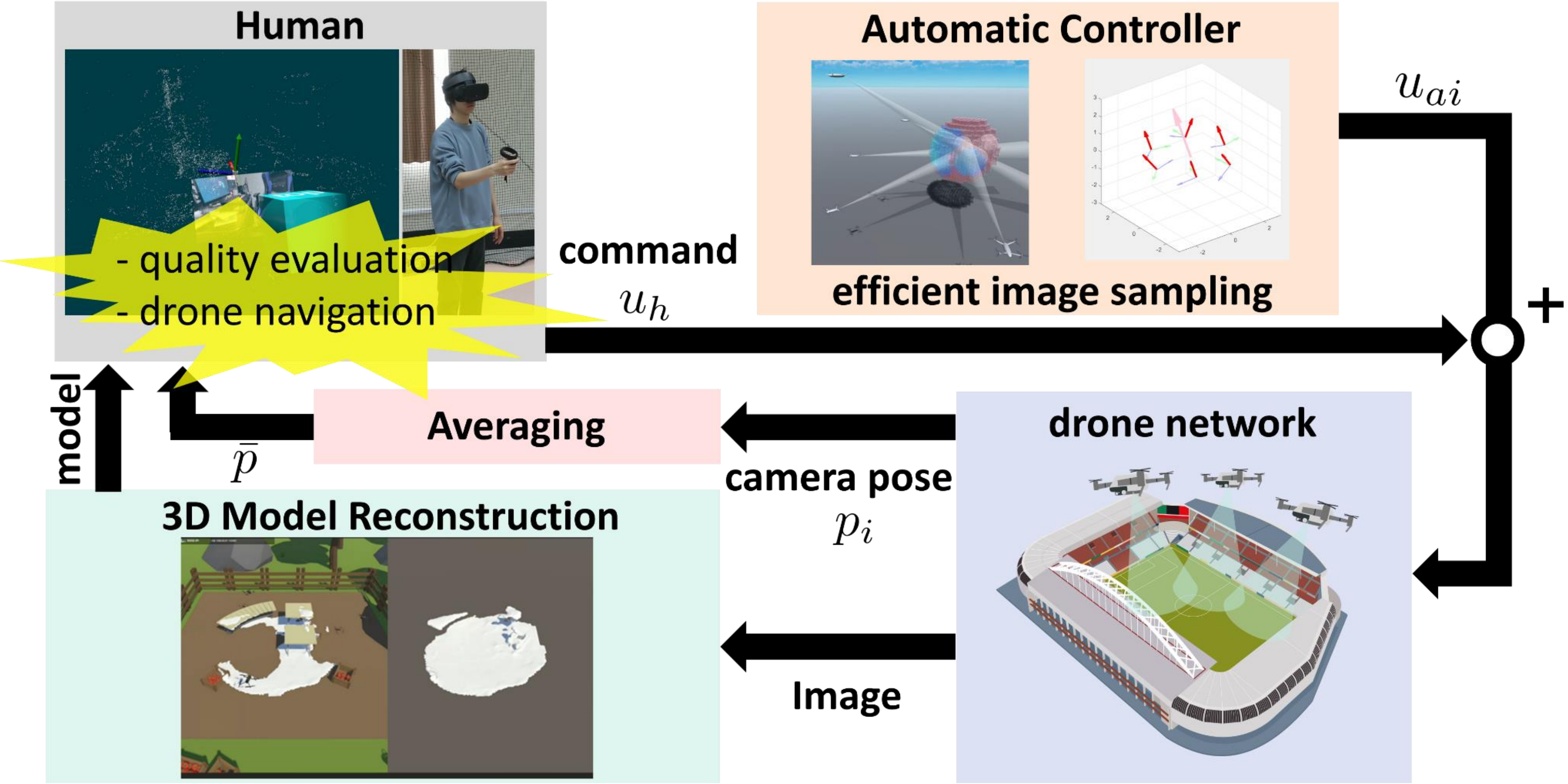






without Real-time map feedback

Human-enabled Coordinated Image Sampling



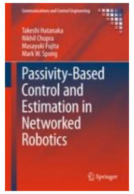
Human-enabled Coordinated Image Sampling

Cyber-Physical-Human Systems

Human-enabled Multi-robot Navigation

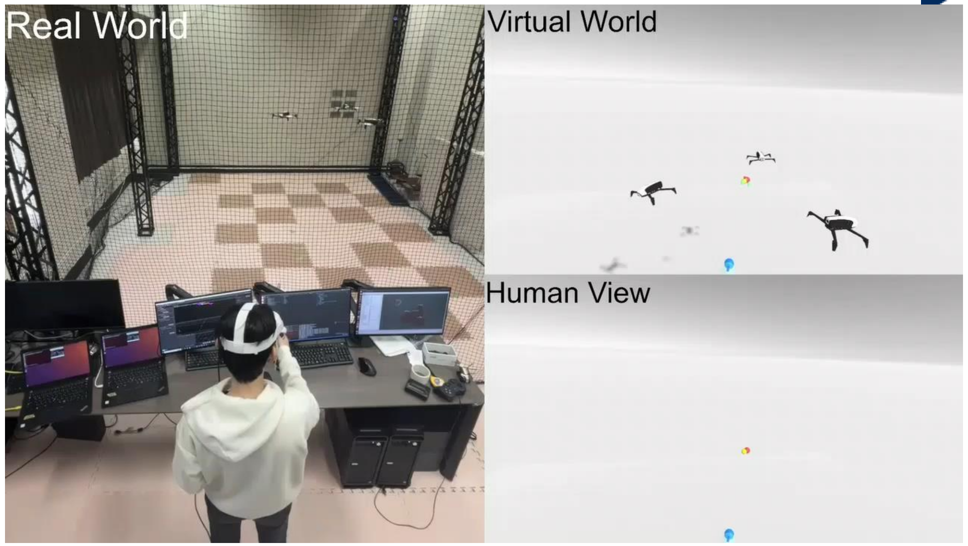
passivity

$$\dot{S} \leq y^T(\tau)u(\tau)$$

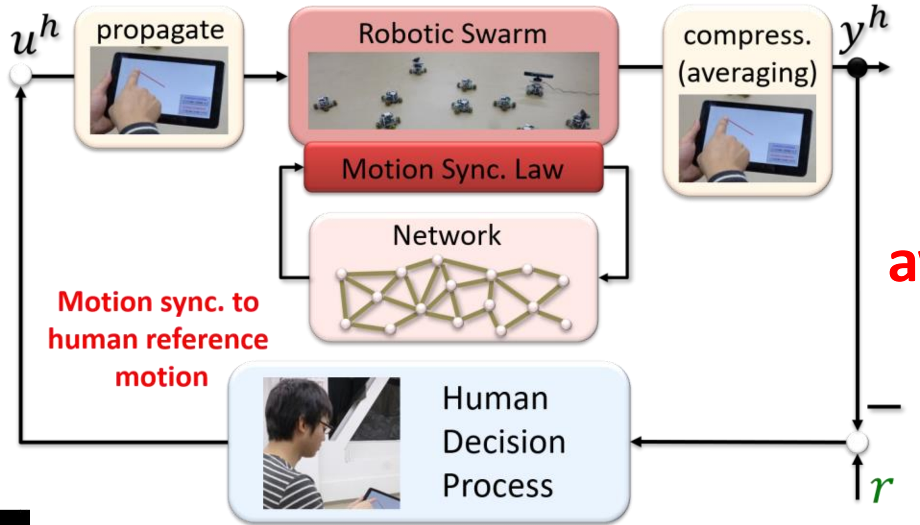


FB connection of passive systems is stable

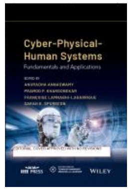
T. Hatanaka, N. Chopra, M. Fujita and M. W. Spong: Passivity-Based Control and Estimation in Networked Robotics, Communications and Control Engineering Series, Springer, 2015.



human-enabled multi-robot navigation

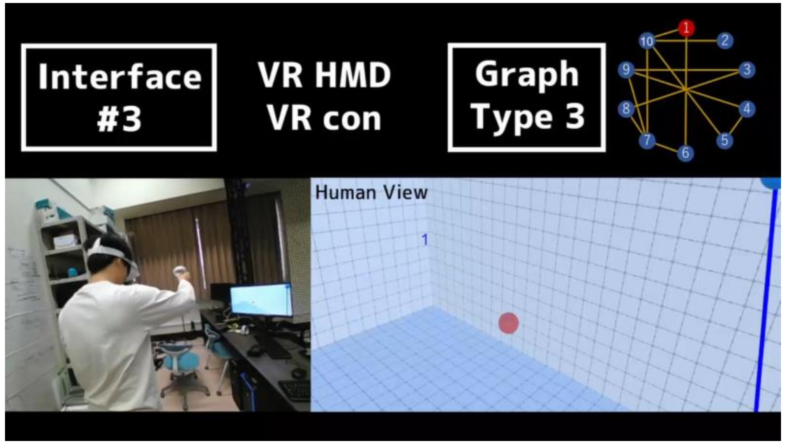


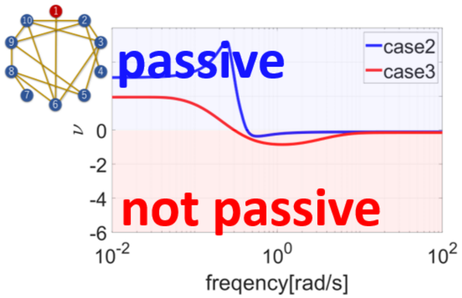
average



T. Hatanaka, J. Yamauchi, M. Fujita, and H. Handa, Contemporary Issues and Advances in Human-Robot Collaborations, Cyber-Physical-Human Systems: Fundamentals and Applications, A. Annaswamy, P.P. Khargonekar, F. Lamnabhi-Lagarrigue, and S.K. Spurgeon (eds.), Wiley, pp. 365-400, 2023

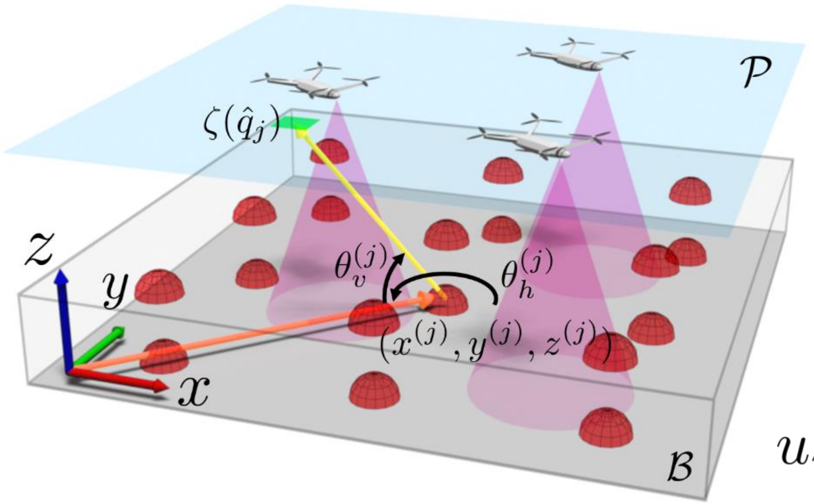
human modeling and passivity analysis



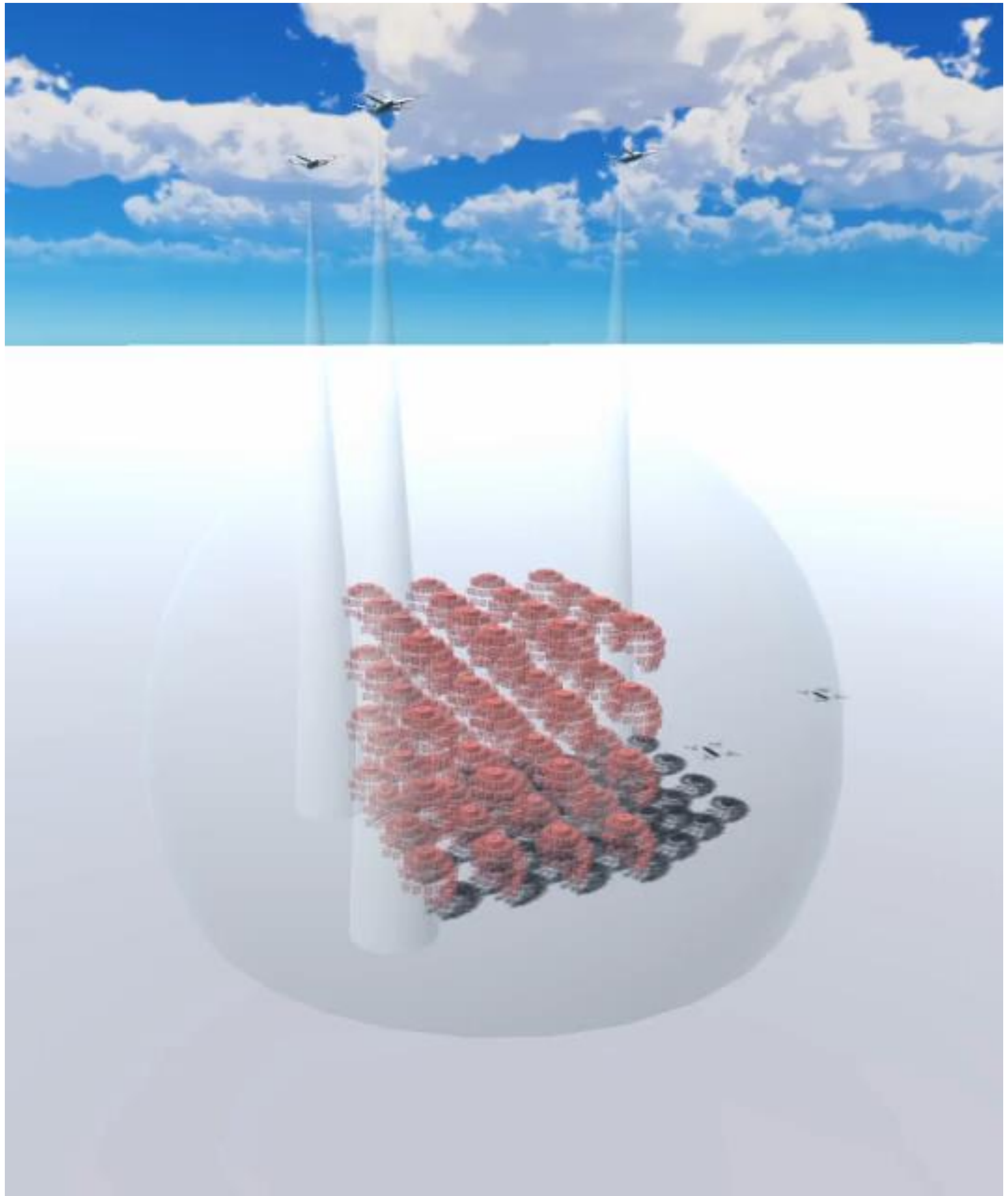


T. Hatanaka, T. Mochizuki, T. Sumino, J.M. Maestre, and N. Chopra, Human Modeling and Passivity Analysis for Semi-autonomous Multi-robot Navigation in Three Dimensions, IEEE Open Journal of Control Systems, Special section on Modeling, Control, and Learning Approaches for Human-Robot Interaction Systems, vol. 3, pp. 45-57, 2024.

Human-enabled Image Sampling



$$u_i = (\dot{x}, \dot{y}, \dot{z}, \dot{\theta}_h, \dot{\theta}_v)$$



navigation

$$u_i = u_{\mathrm{h}} + u_{\mathrm{ms}}$$

human command

motion synchronization (consensus-like algorithm)

coverage

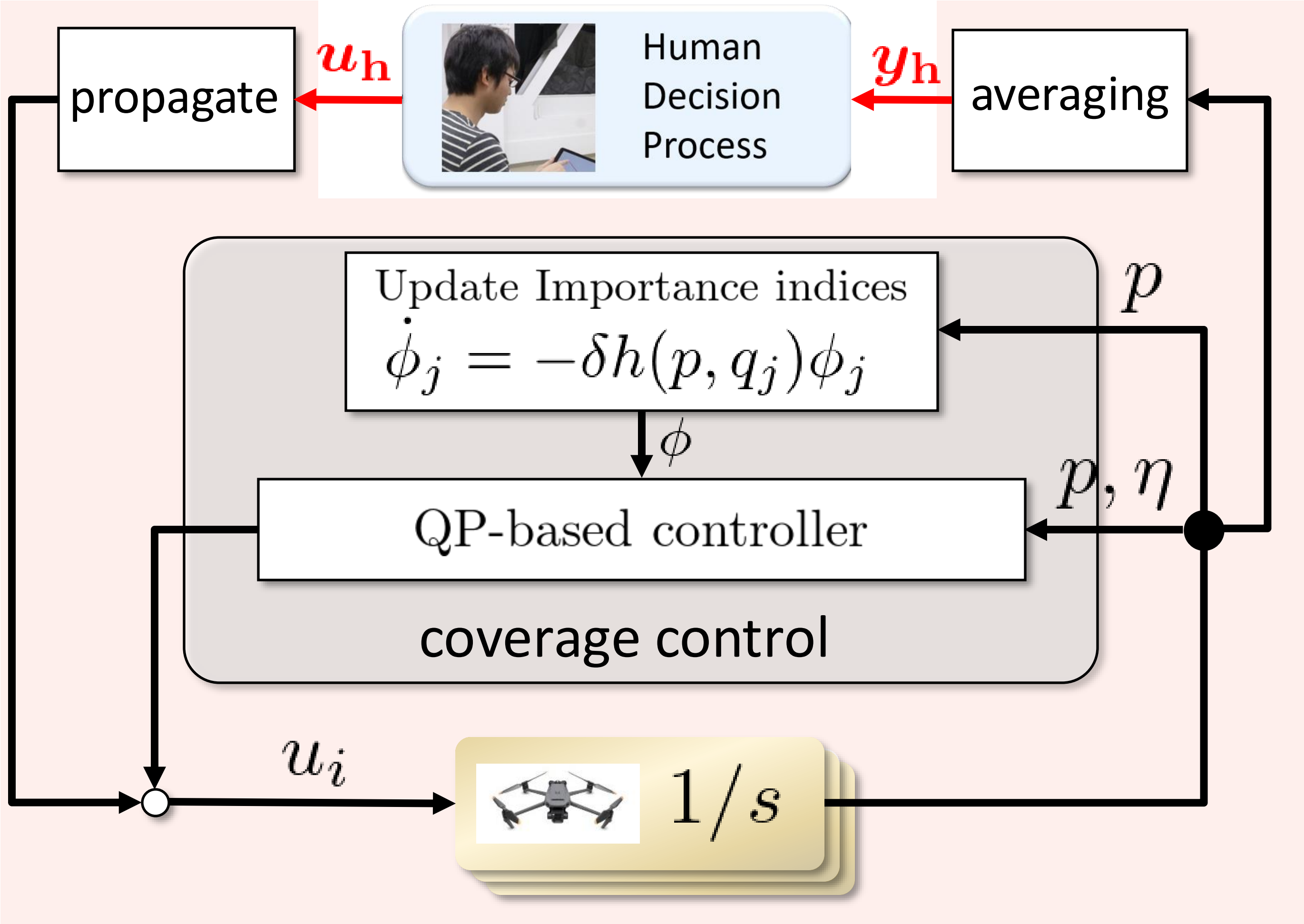
$$u_i = u_{\mathrm{h}} + u_{\mathrm{cc}}$$

human command

coverage control

by using the aforementioned coverage control...

Stealthy Coverage Control



null-space-based interaction

Music, S. , Salvietti, G. , Bude gen. Dohmann, P. , Chinello, F. , Prattichizzo, D. , & Hirche, S. (2017). Human-multi-robot teleoperation for cooperative manipulation tasks using wearable haptic devices. IEEE/RSJ international conference on intelligent robots and systems

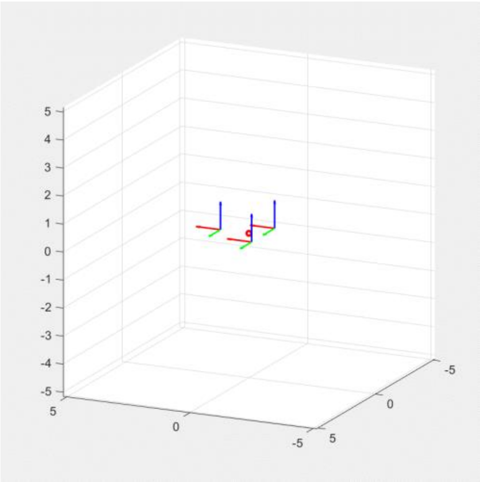
invariant quantities

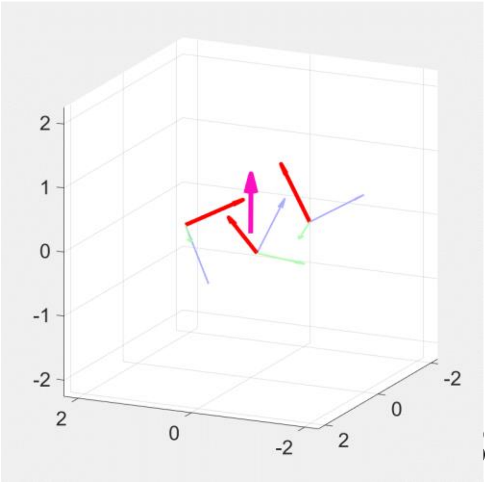
$$\bar{p} = \frac{1}{n}(p_1 + \cdots + p_n) \qquad M = I_n - \frac{1}{n}\mathbf{1}_n\mathbf{1}_n^\top$$

$$\longrightarrow \quad \dot{p} = M u_{\mathrm{cov}}$$

$$\bar{\eta} = \frac{1}{n}(R_1\mathbf{e}_3 + \cdots + R_n\mathbf{e}_3)$$

$$\longrightarrow \quad \dot{\eta} = N(R)v_{\mathrm{cov}}$$



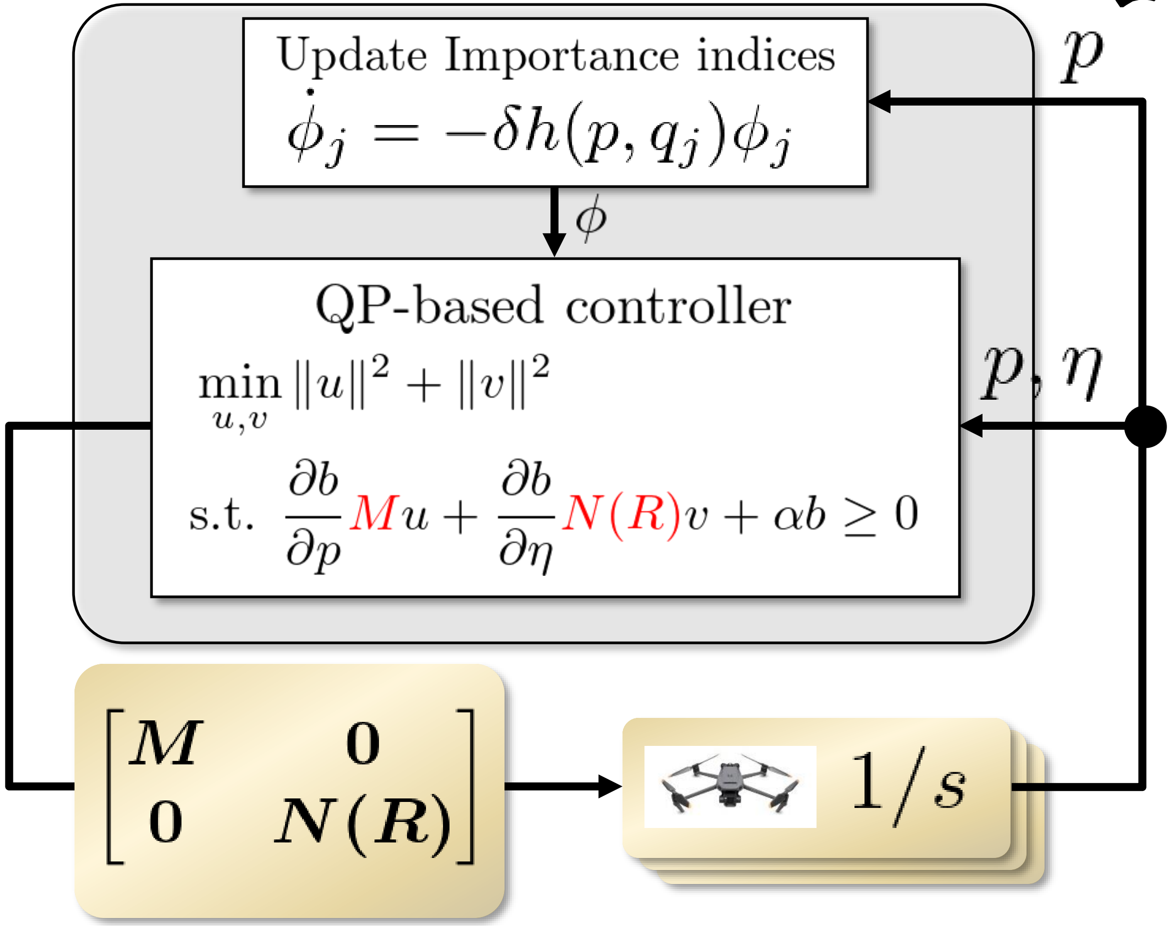


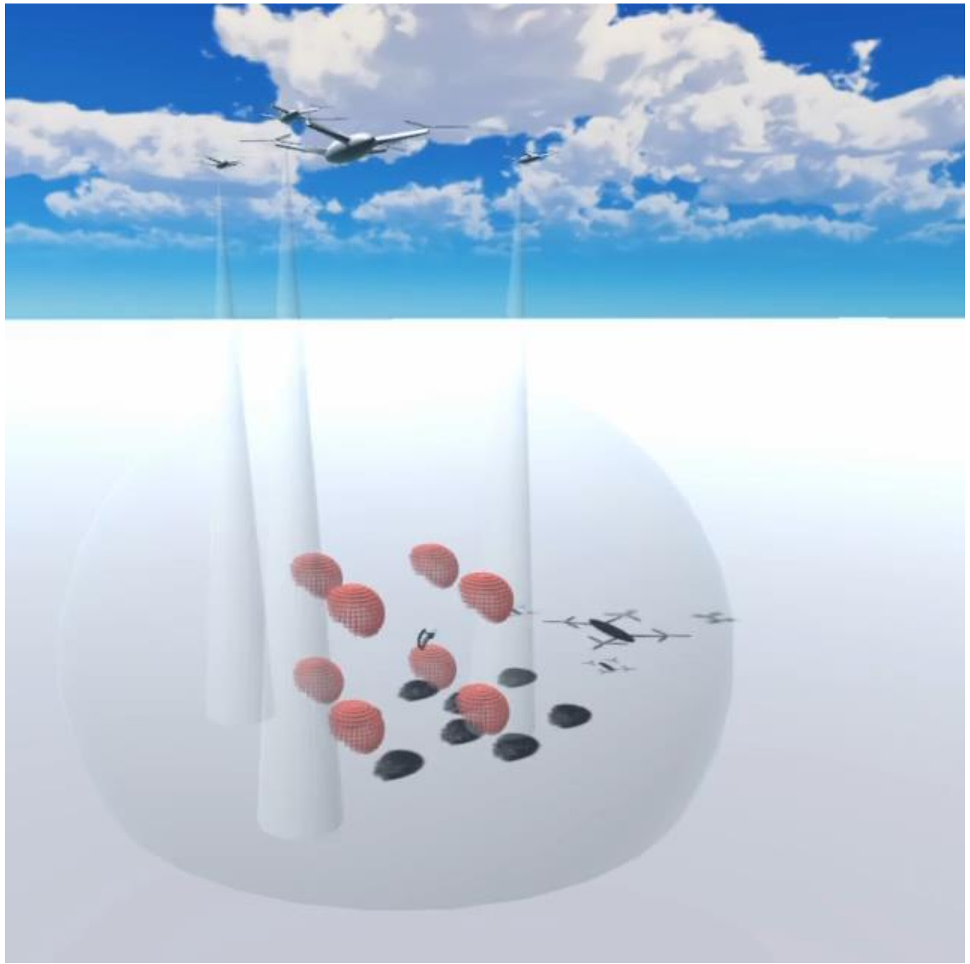
- coverage control violates passivity?
- coverage control degrades operability?

Stealthy Coverage Control

Stability of human-in-the-loop is OK.

just multiplying the matrix may spoil coverage performance guarantee?

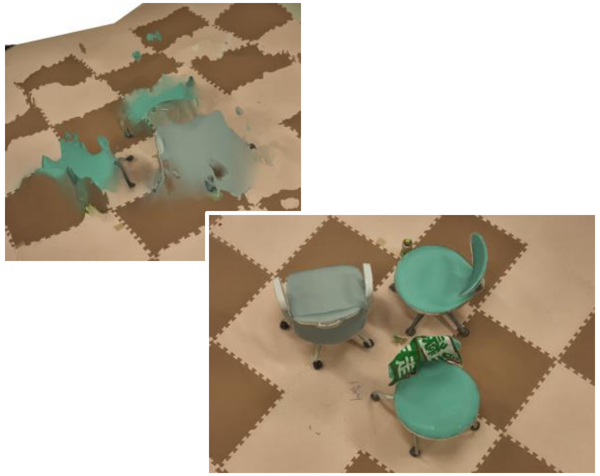




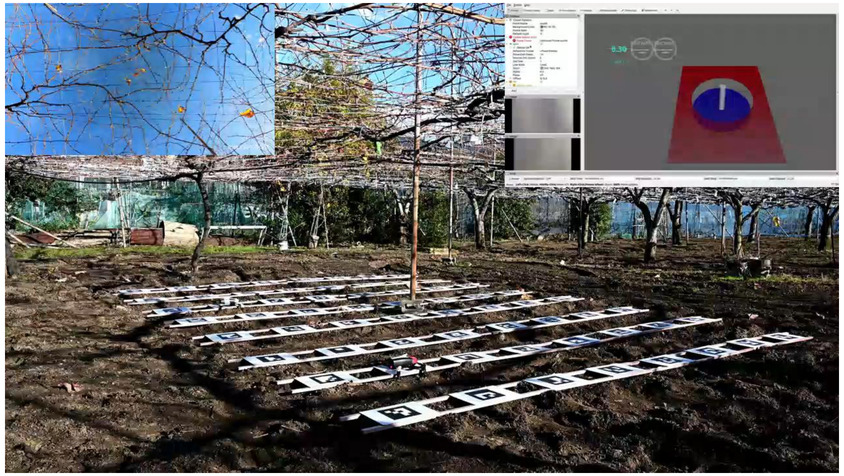
This is still a raw idea, verifications through both simulation and experiments have not been fully completed yet.

Summary

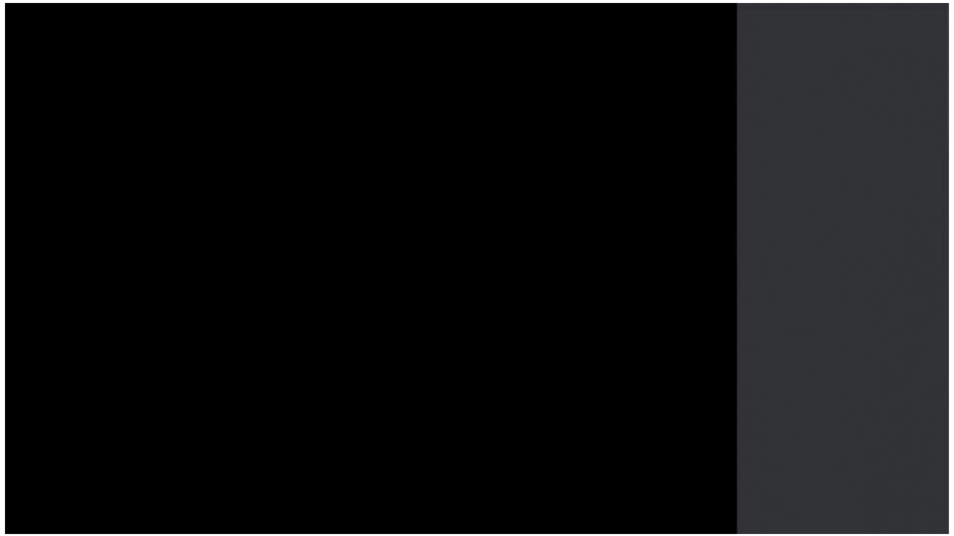
Coverage control enhances 3D model quality



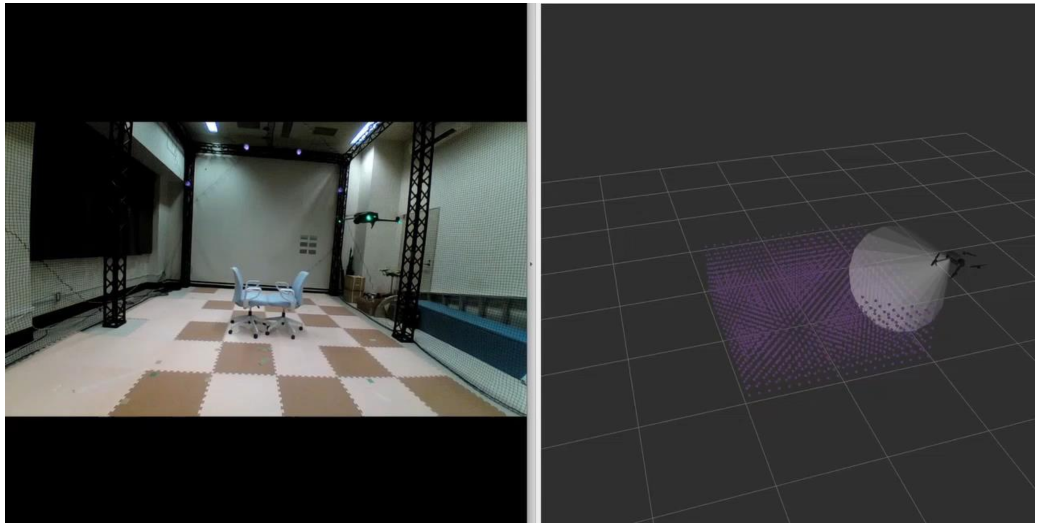
Feasibility in outdoor experiments



Combining MPC solves a problem of geographically dispersed small-scale farms



Real-time 3D mapping techniques may further enhance model accuracy

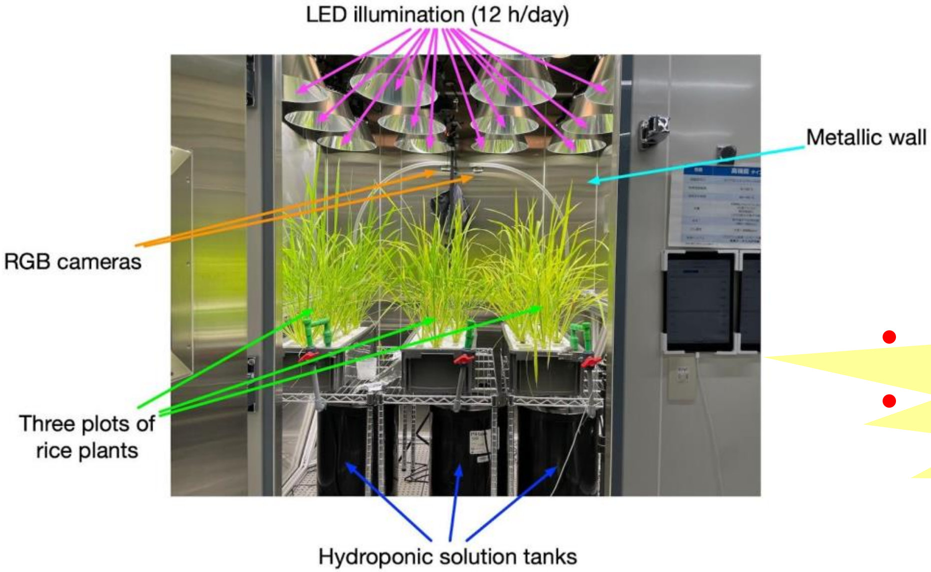


Control in Plant Factory

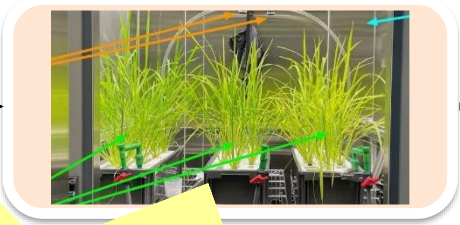
Cabinet Office, Government of Japan, programs for Bridging the gap between R&d and the IDeal society (society 5.0) and Generating Economic and social value

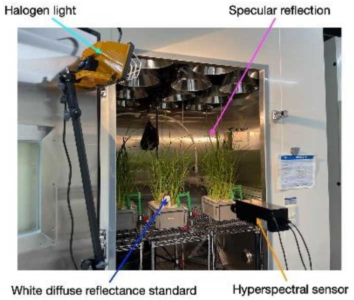
NARO

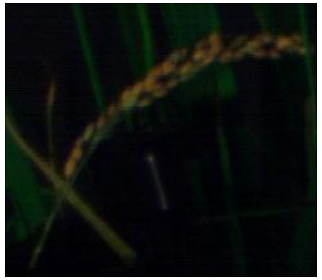
Plant X
COMMUNITY • LIFESTYLE • FOOD



nitrogen
UV-A/B







- sensing by hyperspectral camera
- estimation of internal variables like protein content and stress (flavonoid-a/polyphenol content)

- dynamic modeling by ML
- Real-time control

sparse data in time