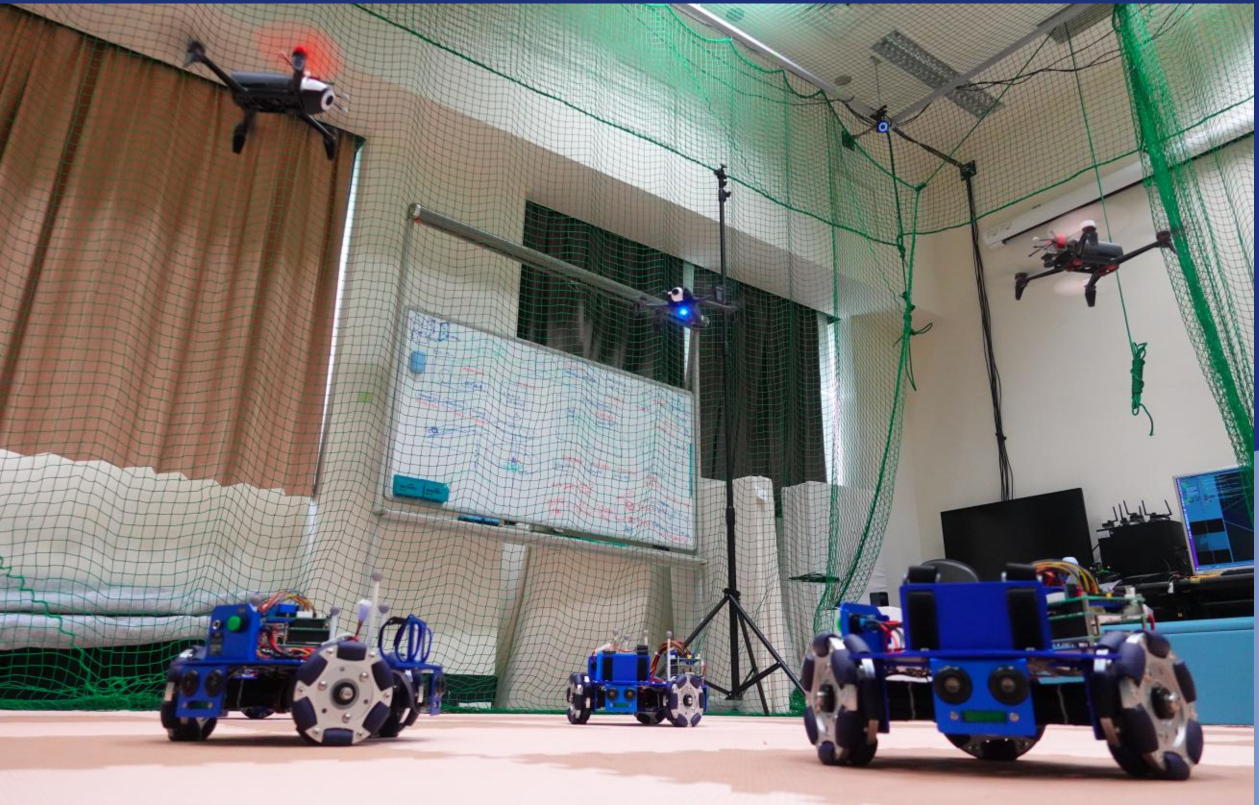
# Adaptive Multi-Drone Coverage Control

## From Autonomy to Human-in-the-Loop Collaboration




**Takeshi Hatanaka**

(Institute of Science Tokyo)

Institute of SCIENCE TOKYO

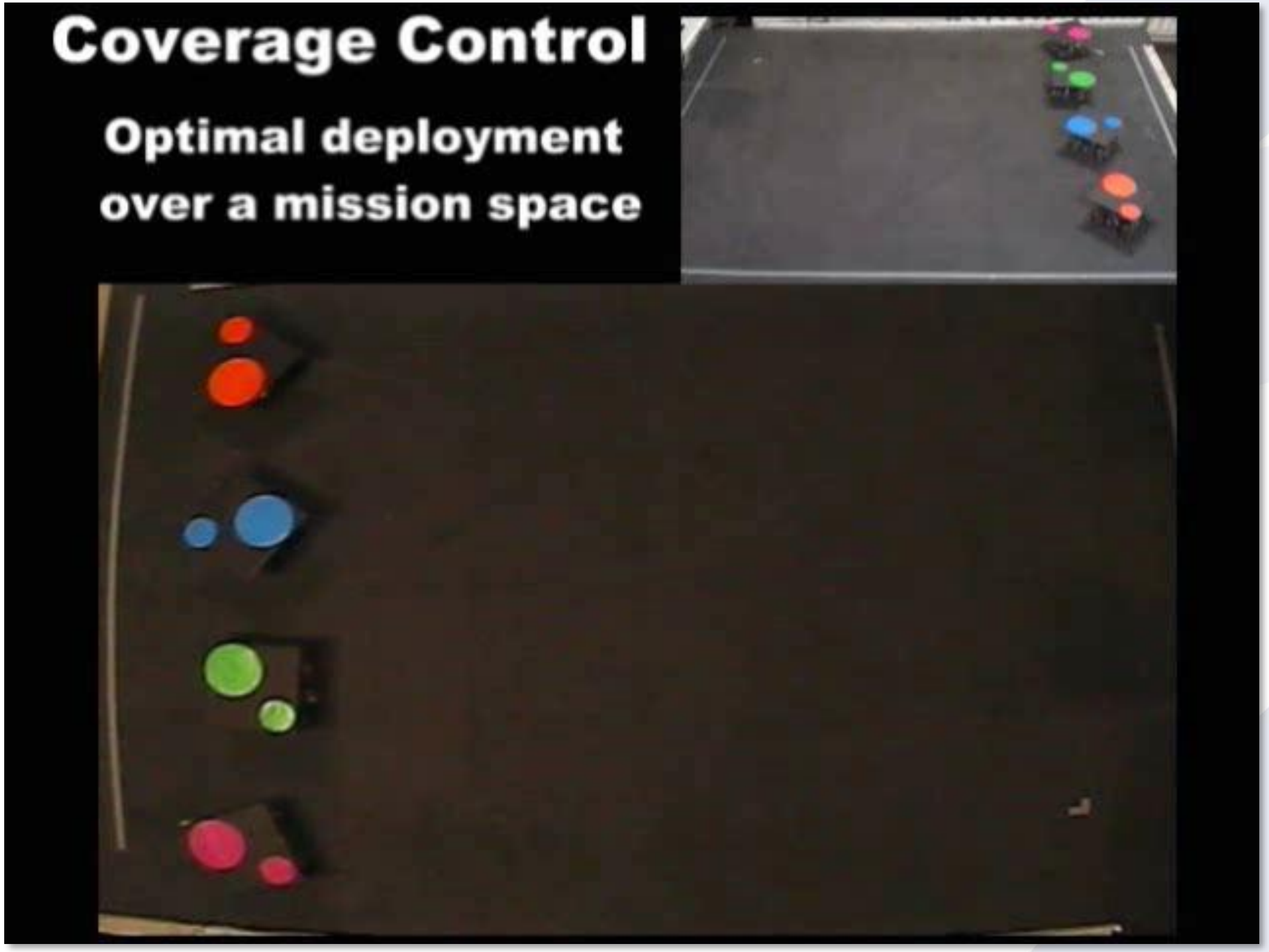


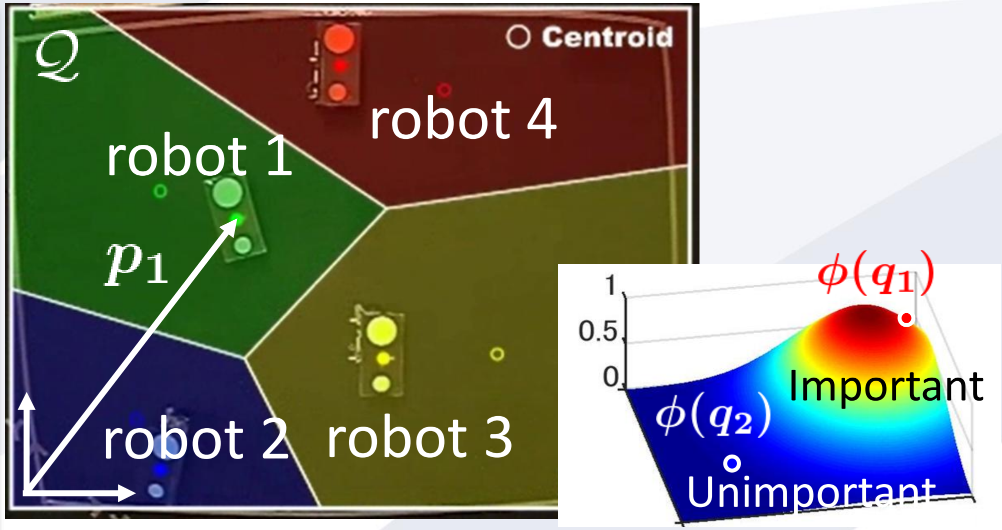
JST ASPIRE "AI-Physical Systems" Kick-Off Meeting

Osaka Metropolitan University

March 3, 2026

# Preliminary: Coverage Control




$$\dot{p}_i = u_i \quad p = \begin{bmatrix} p_1^\top & \cdots & p_n^\top \end{bmatrix}^\top$$

Sensing Performance: $f(p,q)$

**Objective Function**

$$J(p) = \int_{q \in \mathcal{Q}} f(p,q)\phi(q)\,dq$$

**Value of data**

J. Cortes, S. Martinez, T. Karatas, and F. Bullo, Coverage control for mobile sensing networks, IEEE Transactions on Robotics and Automation, vol. 20, no. 2, pp. 243–255, 2004

# Preliminary: Coverage Control

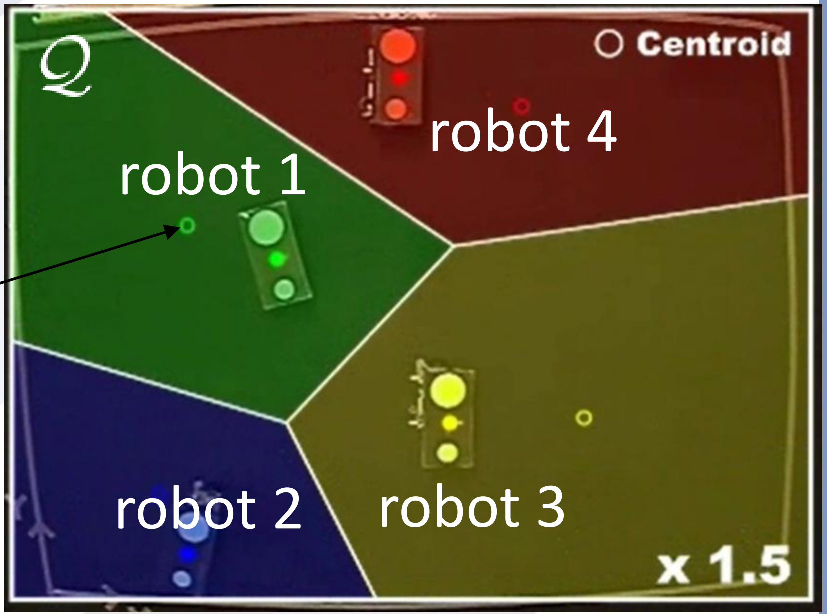
$$f(p,q) = \frac{1}{2}\min_i \|p_i - q\|^2$$

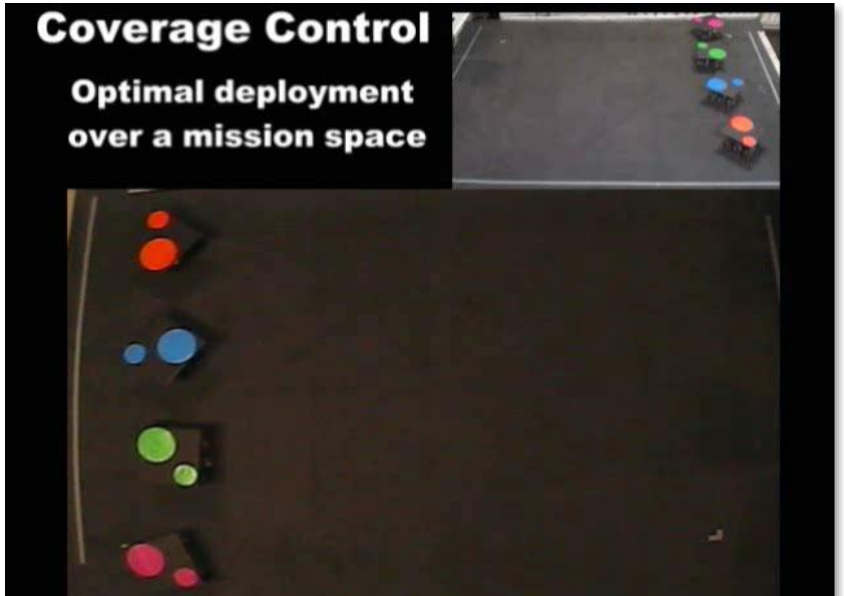
$$u_i = -\frac{\partial J}{\partial p_i}(p) = \underline{M_i(p)(C_i(p) - p_i)}$$

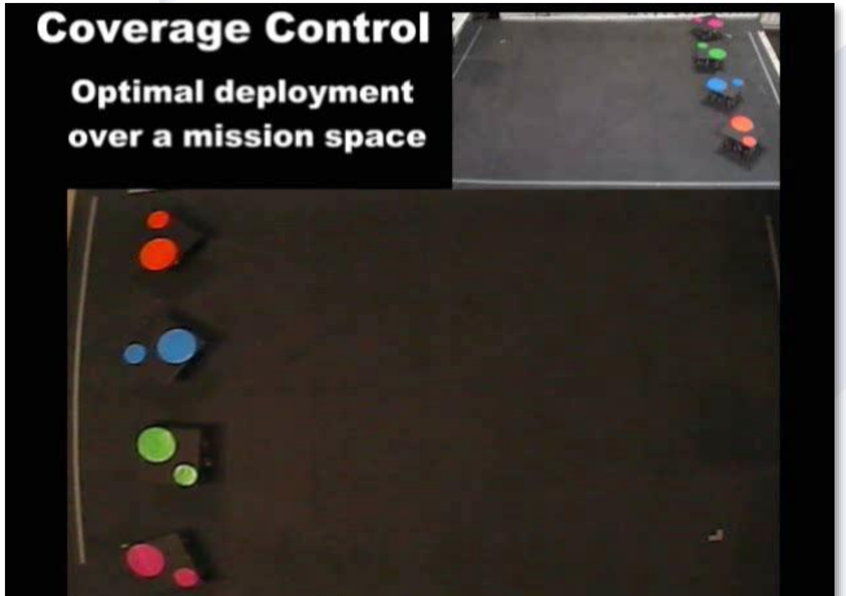
Negative FB: reference = $C_i(p)$

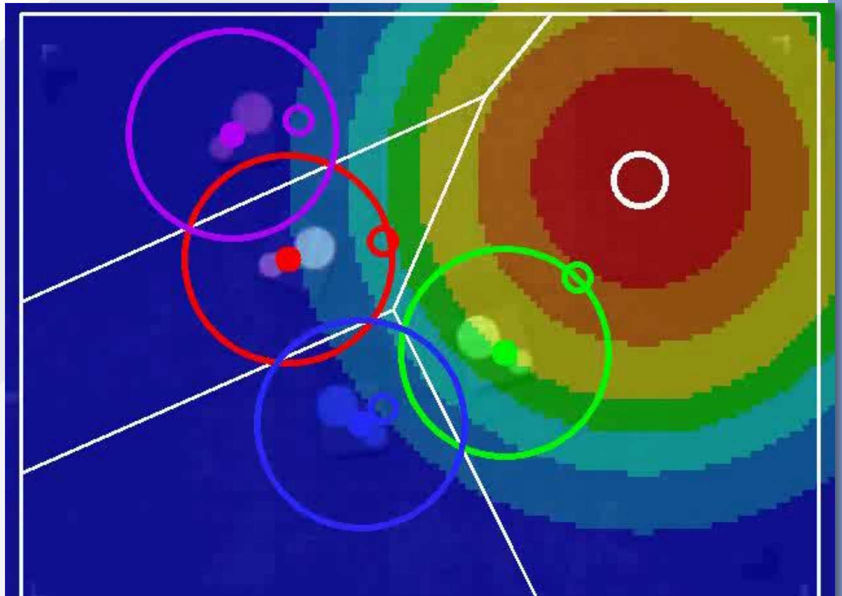
$M_i(p)$ : Area of $\mathcal{V}_i(p)$ $C_i(p)$ : Centroid of $\mathcal{V}_i(p)$

Voronoi Part.: $\mathcal{V}_i(p) = \{q \in \mathcal{Q} | \ \|p_i - q\| \leq \|p_j - q\| \ \forall j\}$



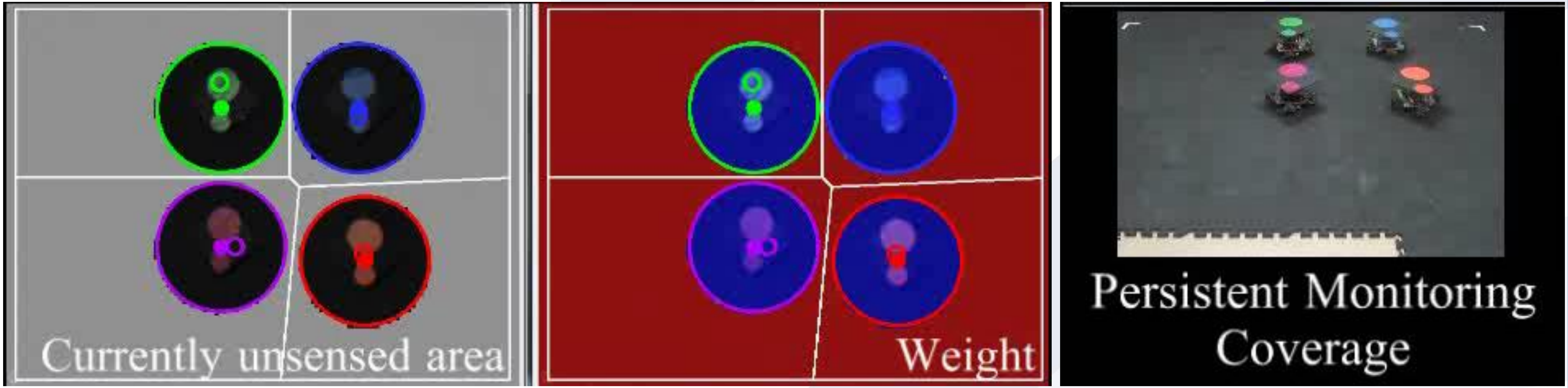
# Preliminary: Pesistent Coverage Control

## Update of importance indices

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

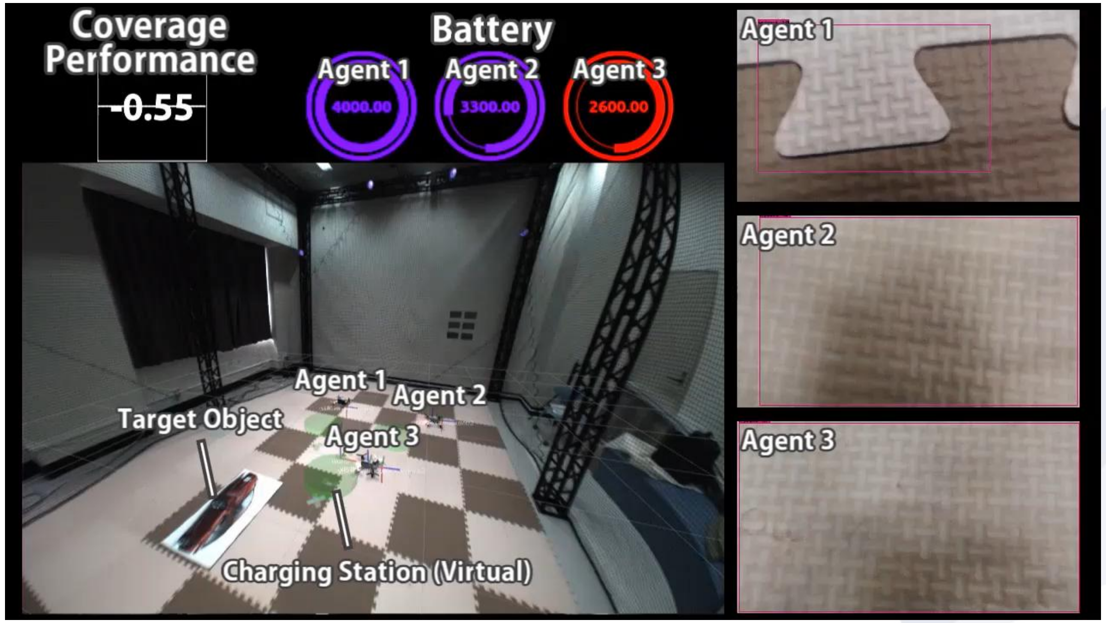
e.g.

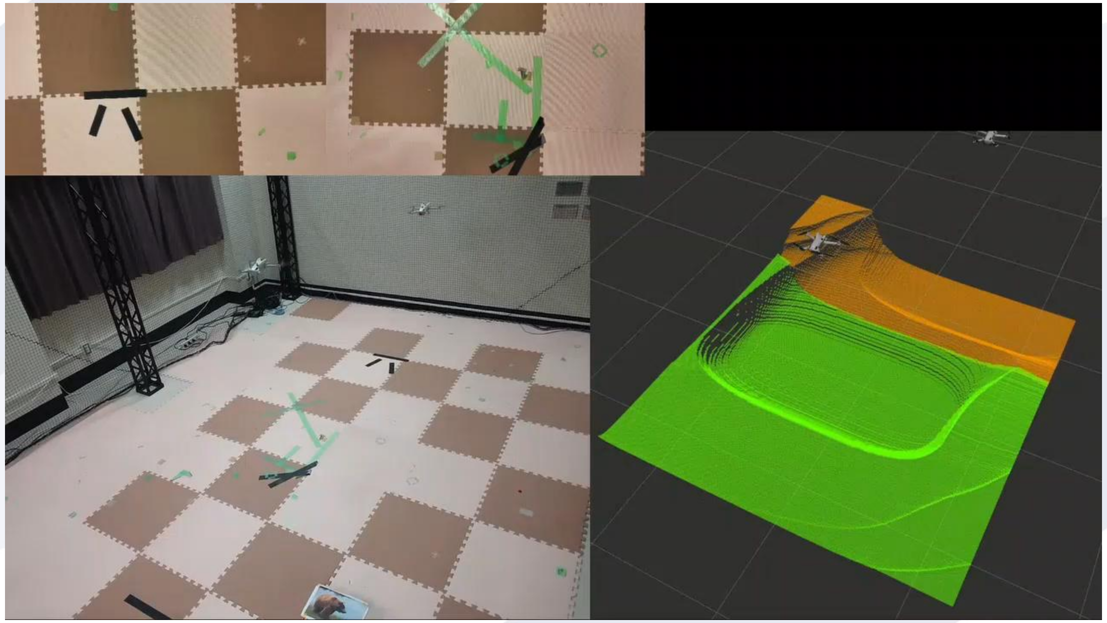
$$\dot{\phi}(q) = \begin{cases} -\delta\phi(q), & \text{if } q \text{ is monitored} \\ \delta(1-\phi(q)), & \text{otherwise} \end{cases}$$

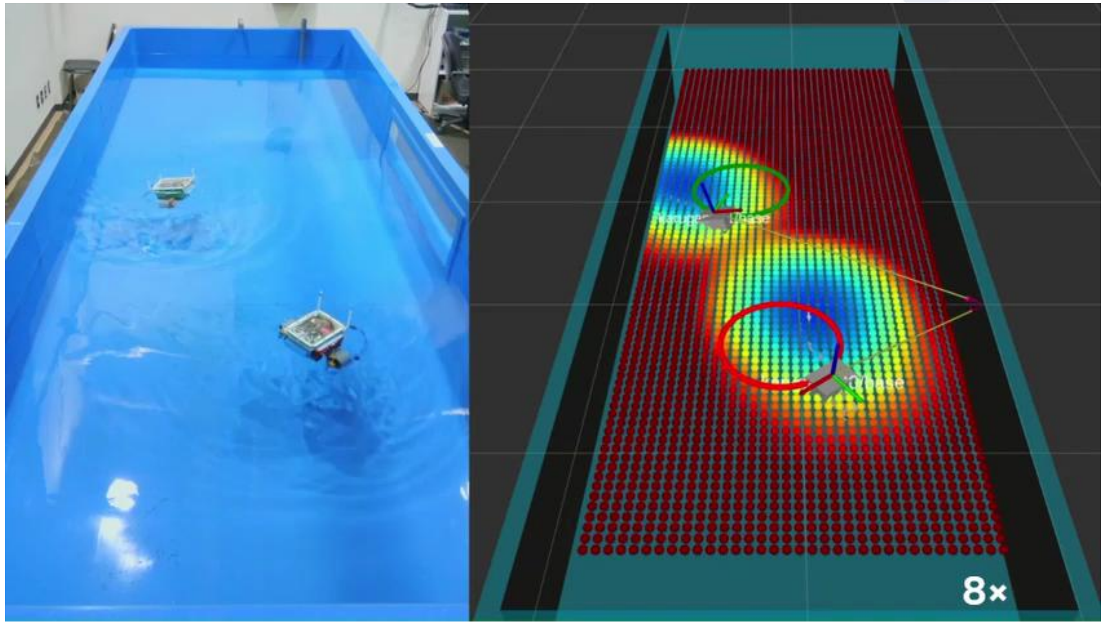


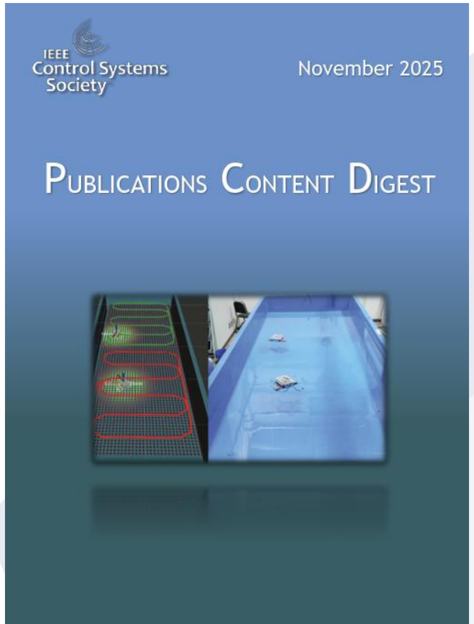

N. Hubel, S. Hirche, A. Gusrialdi, T. Hatanaka, M. Fujita, and O. Sawodny, "Coverage Control with Information Decay in Dynamic Environments," in Proceedings of IFAC WC, pp. 4180–4185, 2008.

# Robot Zoo Sky/Aqua







H. Dan, J. Yamauchi, T. Hatanaka, and M. Fujita, Proc. 4th Proc. IEEE Conference on Control Technology and Applications, 2020
**(Outstanding Student Paper Award)**

Y. Monden, Y. Takizawa, T. Hatanaka, Mediterranean Control Conference 2026, submitted, 2026

T. Oshima, Y. Toyomoto, and T. Hatanaka, Proc. 8th IEEE Conference on Control Technology and Applications, 2024 **(Best Student Paper Award)**

Y. Toyomoto, T. Oshima, K. Oishi, J.M. Maestre, and T. Hatanaka, IEEE Transactions on Control Systems Technology, vol. 33, no. 6, pp. 2037-2051, 2025.

# Agriculture 4.0

Institute of SCIENCE TOKYO

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

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

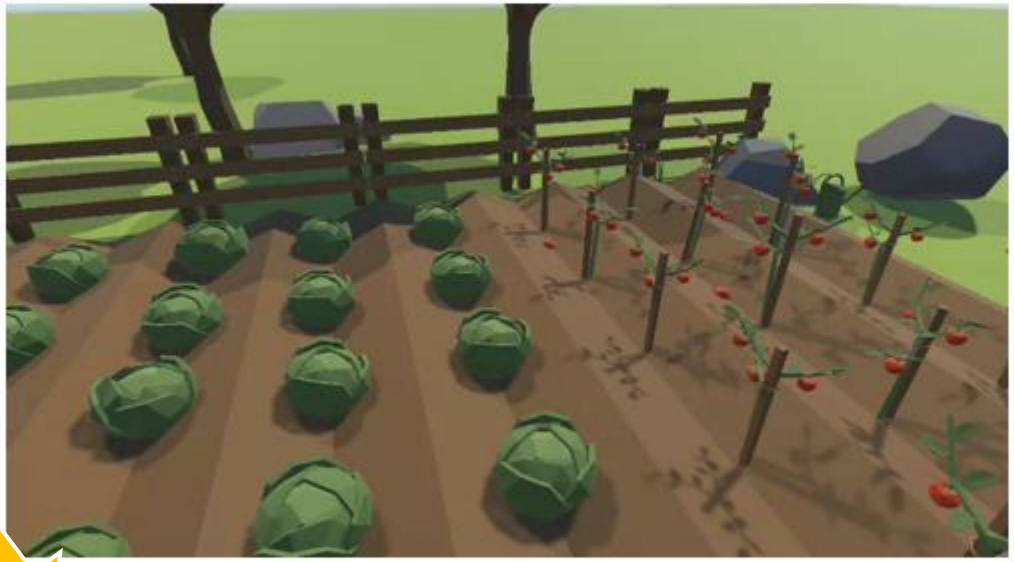
## 2.4 Automation und Robotik (Automation and Robotics)

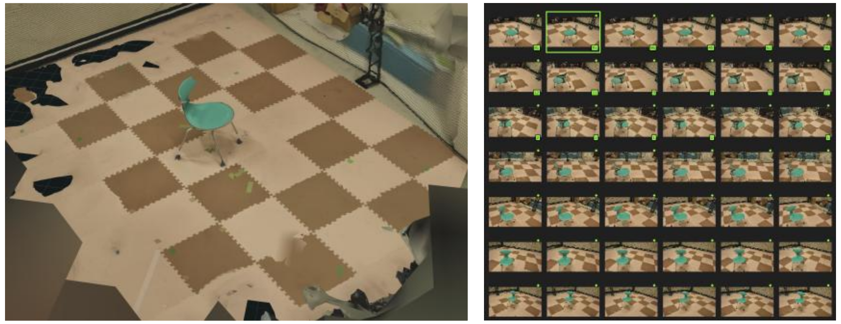
It is already becoming apparent that autonomous robots will mostly be **small in size and electrically driven**. This will lead to considerable reductions in investment costs and vehicle weights. The lower the acquisition and investment costs, the lower the area performance can be. This effect helps 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 less energy. Such devices are lightweight and therefore gentle on the soil.


**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.**

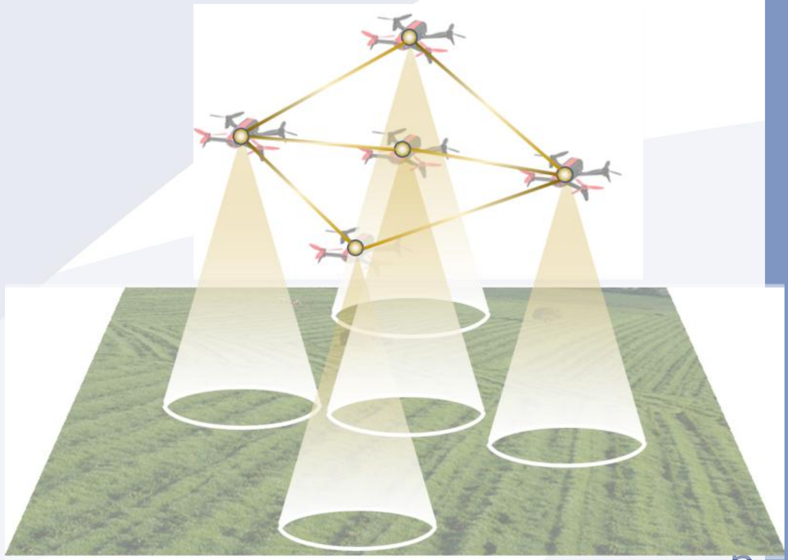
# Coordinated Image Sampling







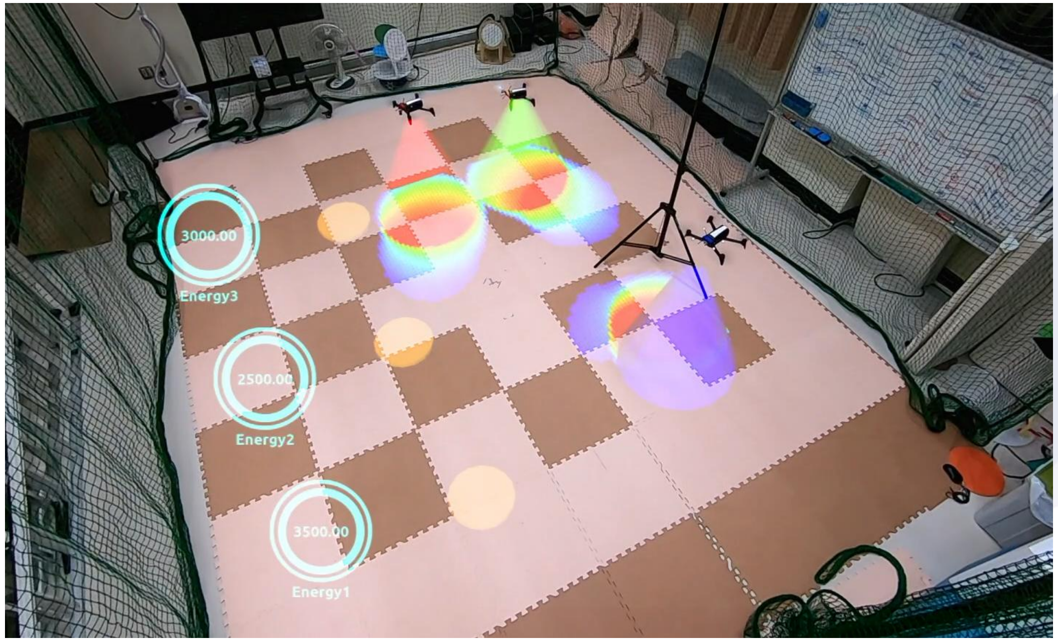
Structure from Motion (SfM)



# Persistent Coverage vs Image Sampling

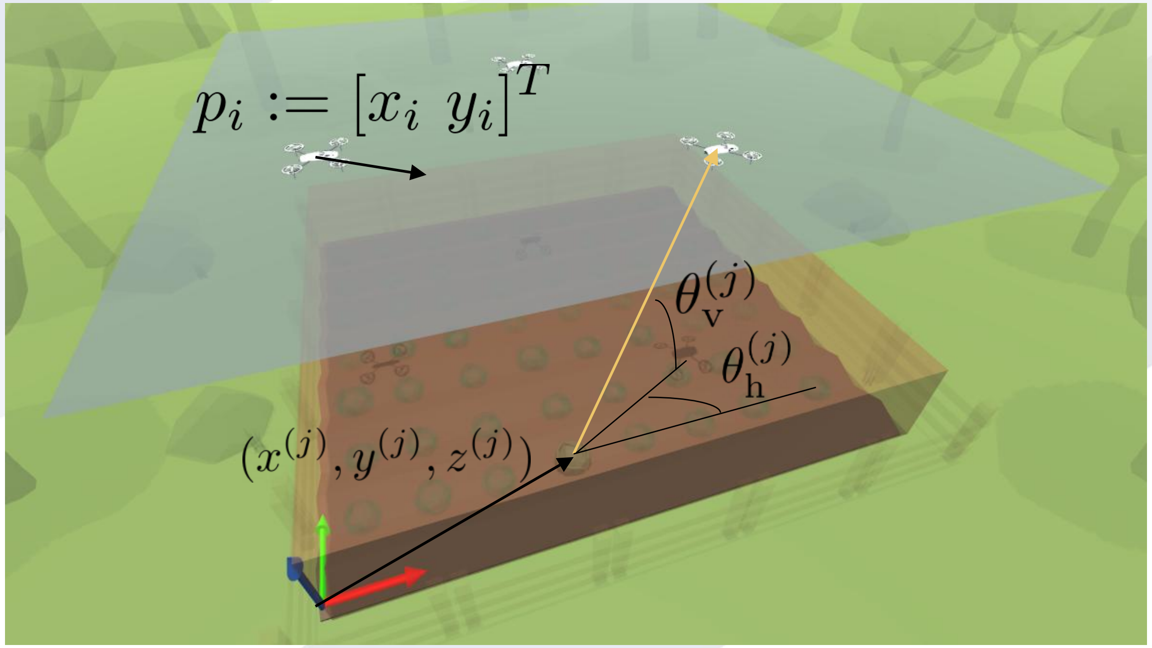
Institute of SCIENCE TOKYO

**capture within FOV (2D)**




**revisit many times**

**sample from various angles (5D)**




**sampling just once is enough**

# Problem Formulation



<u>drone dynamics</u>

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

<u>observation points</u>

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

<u>sensing performance</u>

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

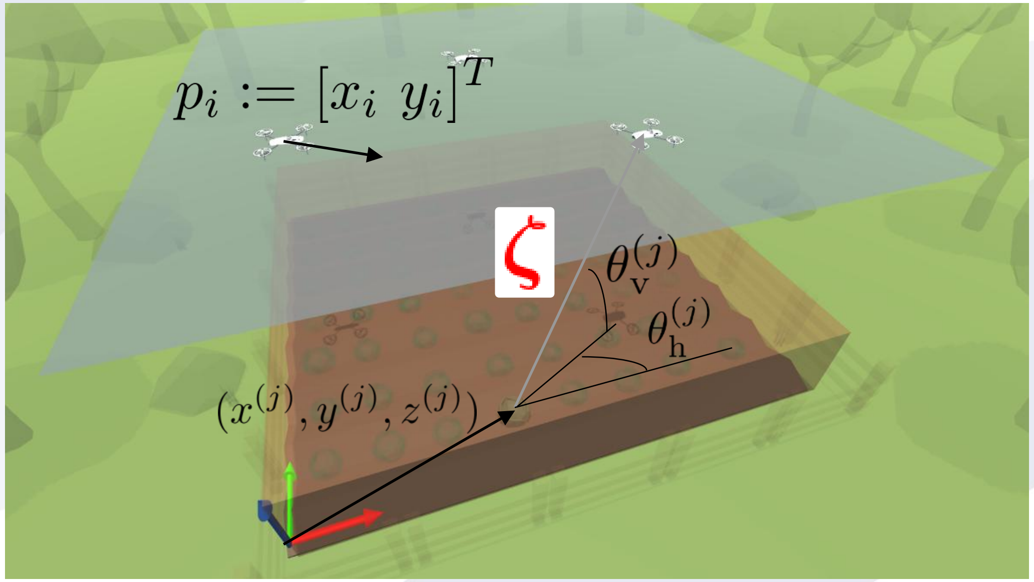
**<u>density update</u>**

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

monotonically decreasing

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

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.



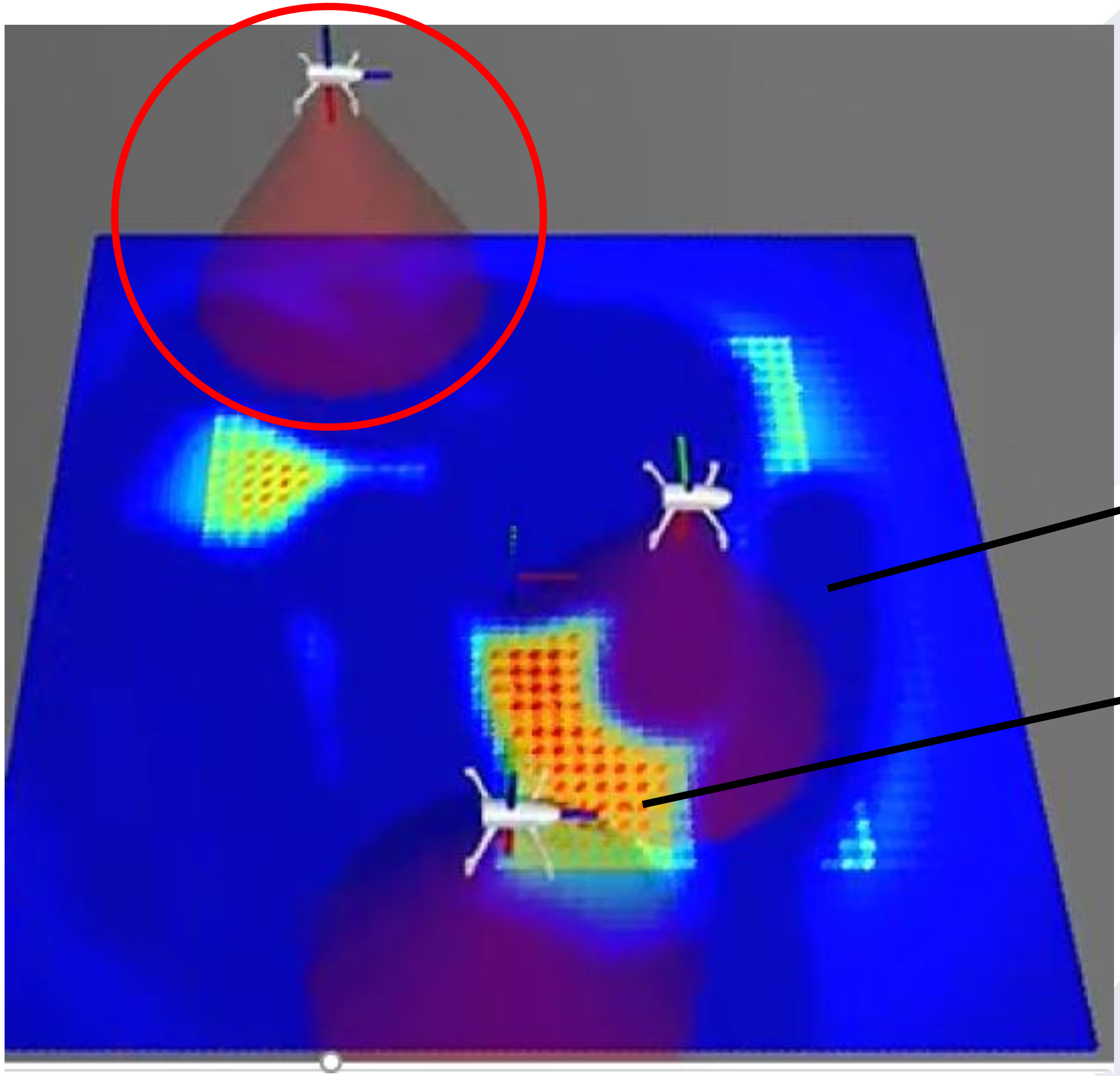

$$\zeta : [x \; y \; z \; \theta_{\mathrm{h}} \; \theta_{\mathrm{v}}]^T \mapsto \begin{bmatrix} x - (z_c - z)\tan\left(\frac{\pi}{2} - \theta_{\mathrm{v}}\right)\cos\theta_{\mathrm{h}} \\ y - (z_c - z)\tan\left(\frac{\pi}{2} - \theta_{\mathrm{v}}\right)\sin\theta_{\mathrm{h}} \end{bmatrix}$$

**<u>objective function</u>** $J = \sum_{j=1}^{m} \phi_j$

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

# Difficulties in Gradient-based Method

Institute of SCIENCE TOKYO



**sampling just once is enough**

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

**monotonically decreasing**

well-observed area

unobserved area

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

# Angle-aware Coverage Control



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

**Constraint-based specification**

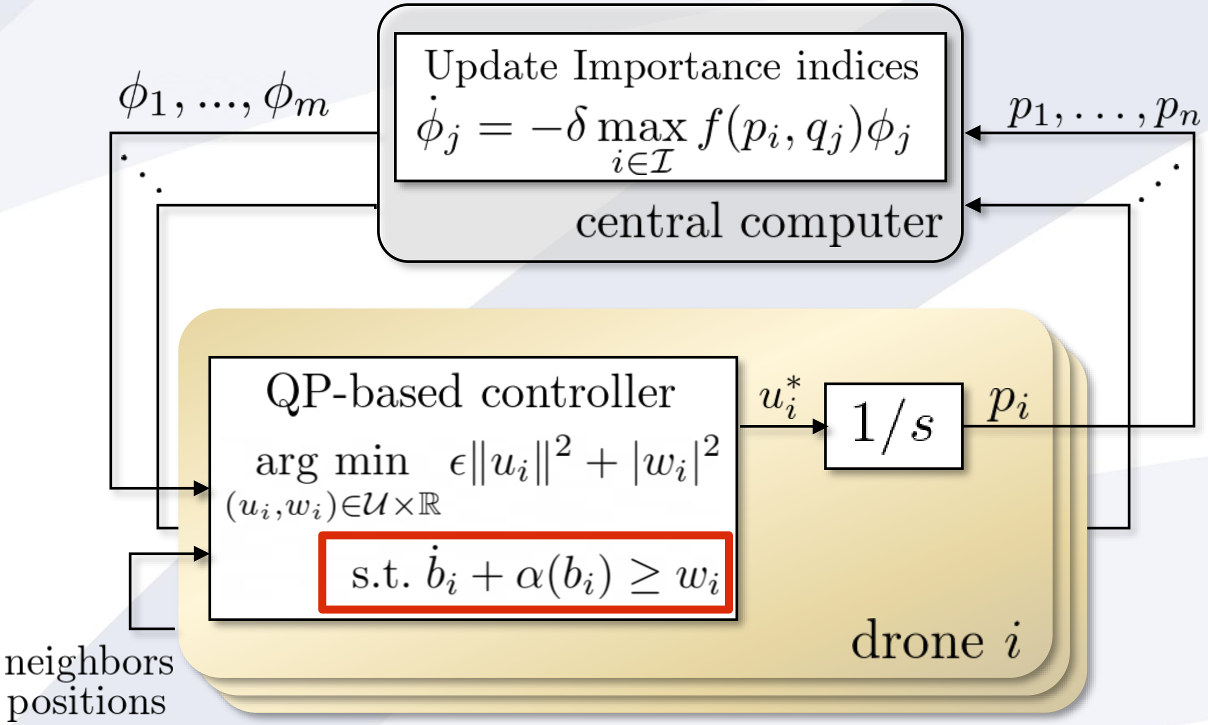
$$\dot{J} \le -\gamma \Leftrightarrow b = -\dot{J} - \gamma \ge 0$$

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

<u>local constraint</u> $-I_i \le -\gamma/n$

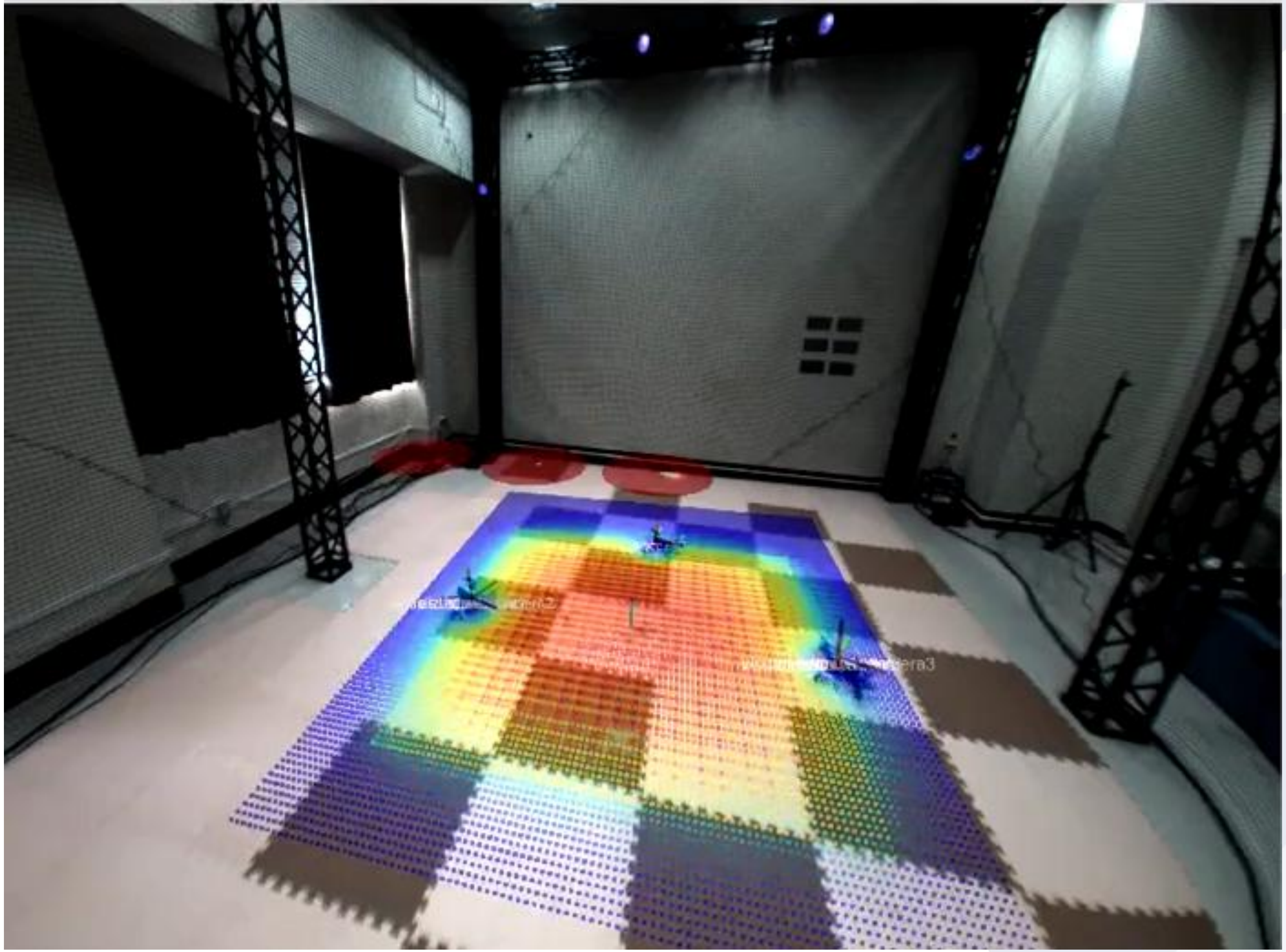
<u>control barrier-like function</u>

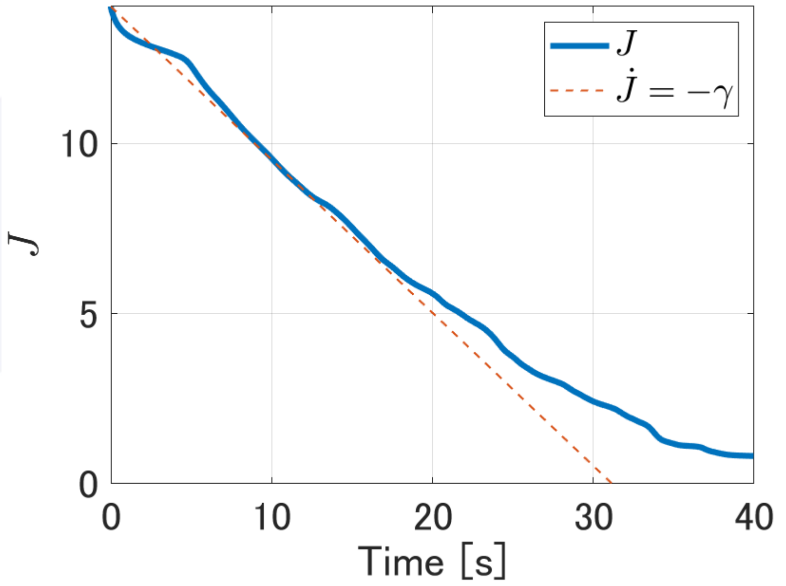
$$b_i = I_i - \gamma/n \ge 0$$

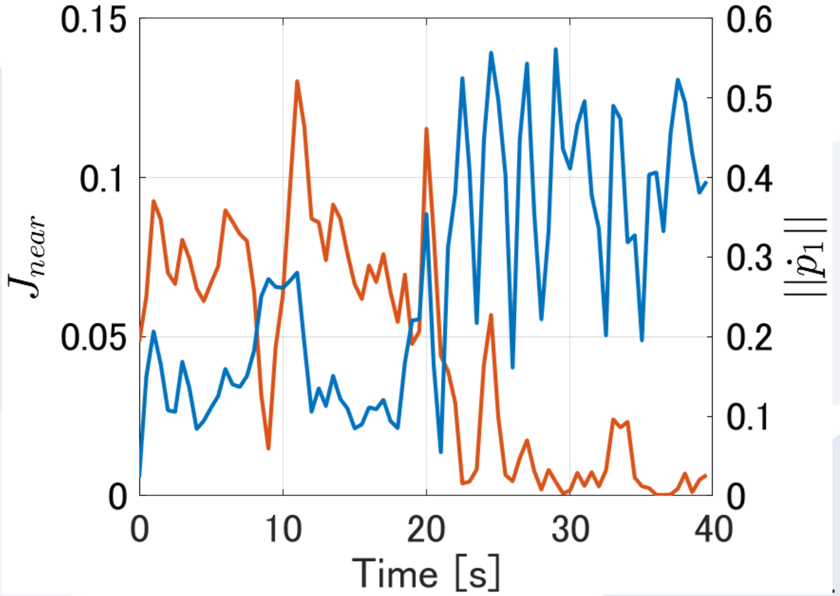



T. Shimizu, S. Yamashita, T. Hatanaka, K. Uto, M. Mammarella, and F. Dabbene, Angle-aware Coverage Control for 3D Map Reconstruction with Drone Networks, IEEE Control Systems Letters, vol. 6, pp. 1831-1836, 2022

# Angle-aware Coverage Control





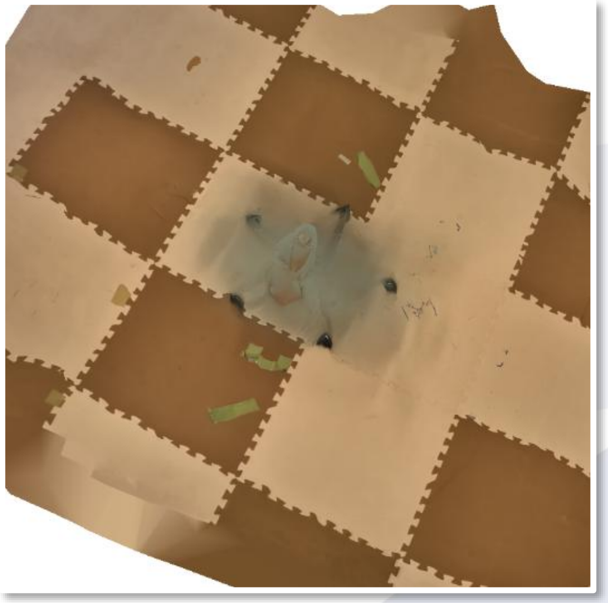
# Angle-aware Coverage Control

Persistent Coverage Control

**Angle-aware Coverage Control**

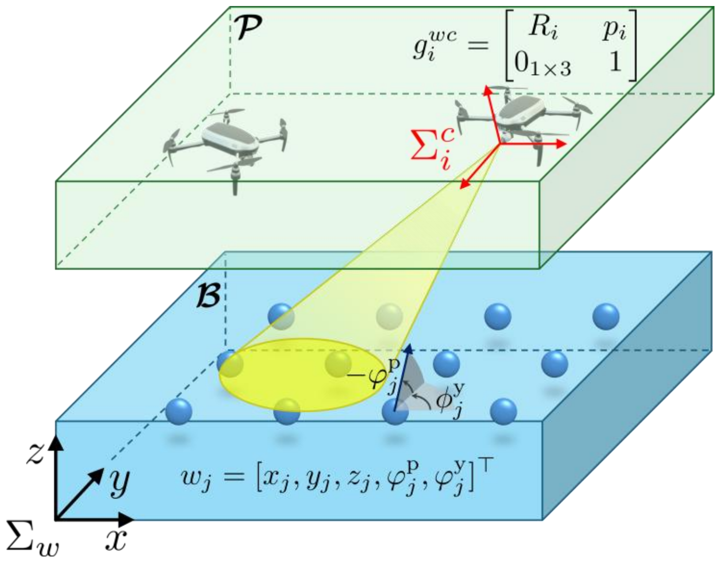
M. Suenaga, T. Shimizu, T. Hatanaka, K. Uto, M. Mammarella, and F. Dabbene, Proc. 2022 IEEE CCTA, pp. 327-333, 2022

degradation in the presence of an object



# Full-3D Angle-aware Coverage Control






rigid-body motion

$$\dot{g}_i^{wc} = g_i^{wc} \hat{V}_i^c$$

$$g_i^{wc} = \begin{bmatrix} R_i & p_i \\ \mathbf{0}_{1\times 3} & 1 \end{bmatrix} \in SE(3).$$

$$\hat{V}_i^c = \begin{bmatrix} \hat{\omega}_i^c & v_i^c \\ \mathbf{0}_{1\times 3} & 0 \end{bmatrix} \in se(3)$$

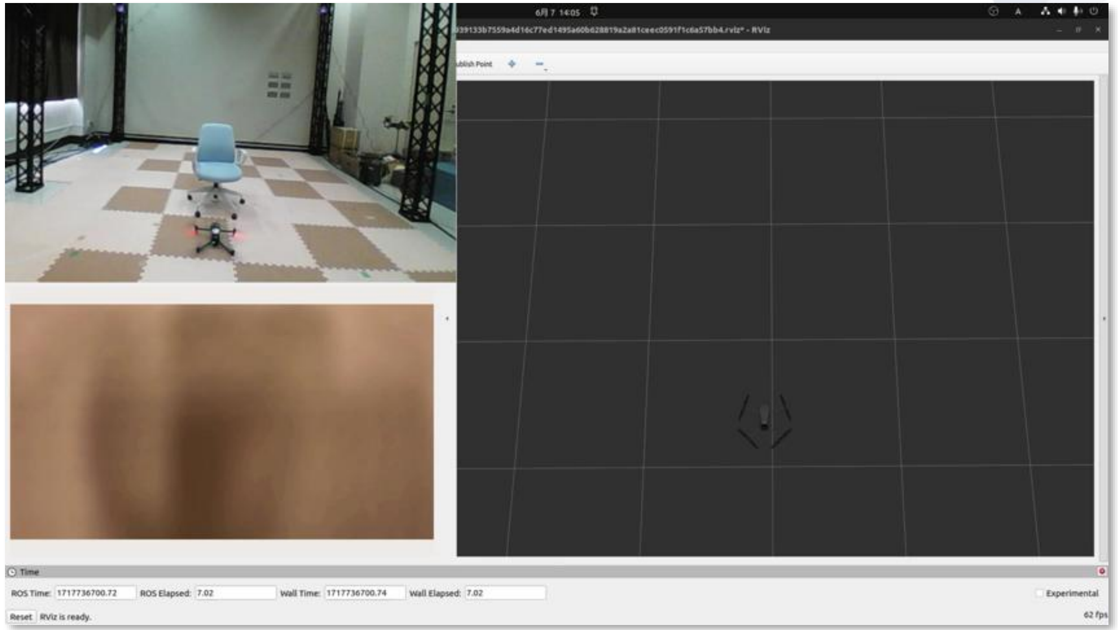
T. Hatanaka, N. Chopra, M. Fujita and M. W. Spong, Passivity-Based Control and Estimation in Networked Robotics, Communications and Control Engineering Series, Springer, 2015.

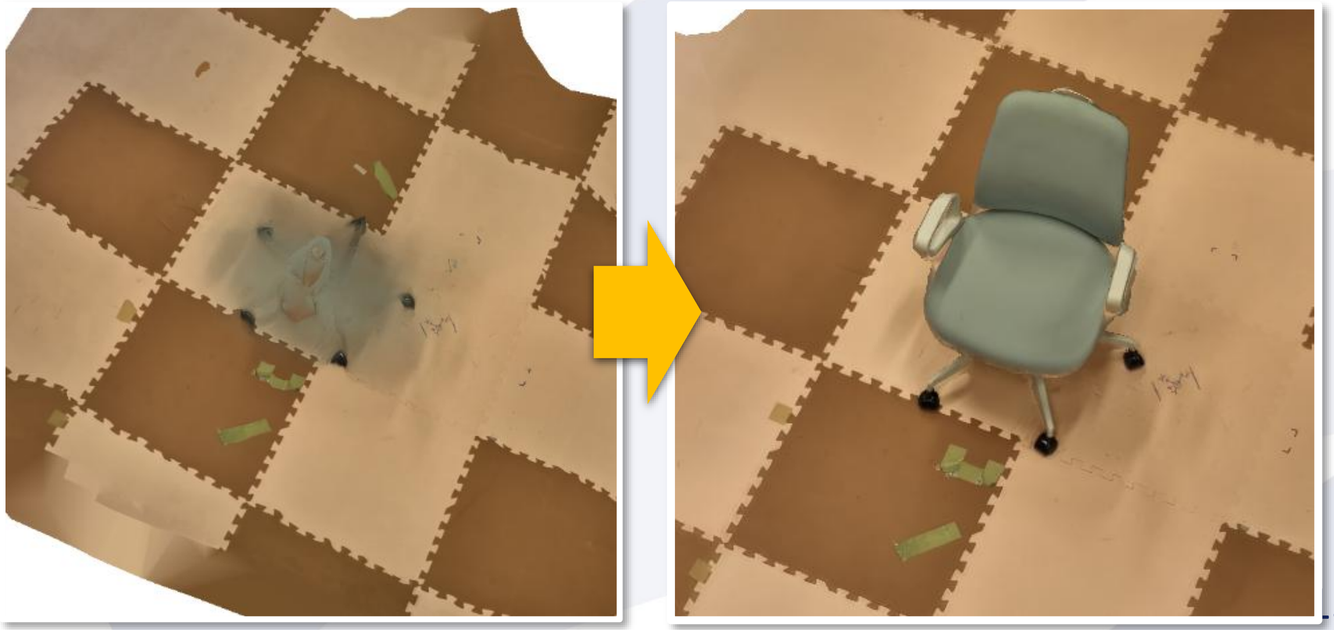
$$\underset{V_i^c,\ \lambda_i}{\text{minimize}} \quad \|V_i^c\|^2 + \lambda_i^2$$

$$\text{subject to} \quad \xi_{1i} V_i^c + \xi_{2i} \geq \beta \lambda_i$$

$$\xi_{1i} = \sum_{j \in \mathcal{V}_i(g^{wc})} \delta\phi_j \sum_{l=1}^{4} \sum_{k=1}^{3} \frac{\partial h_j(g_i^{wc})}{\partial(\mathbf{e}_k^\top g_i^{wc} \mathbf{e}_l)} \mathbf{e}_k^\top g_i^{wc} E_l,$$

$$\xi_{2i} = \sum_{j \in \mathcal{V}_i(g^{wc})} \delta h_j(g_i^{wc}) \phi_j \{\gamma - \delta h_j(g_i^{wc})\} + ab_i$$



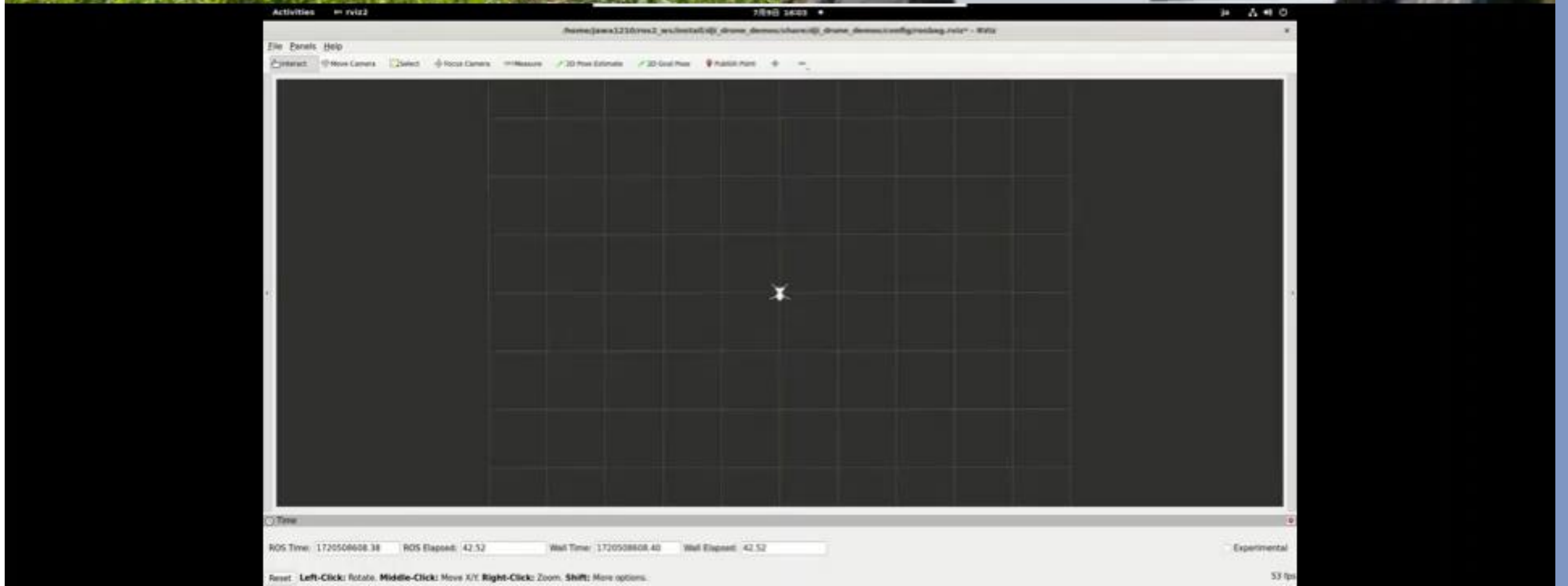



# Field Experiment in Campus

Institute of SCIENCE TOKYO

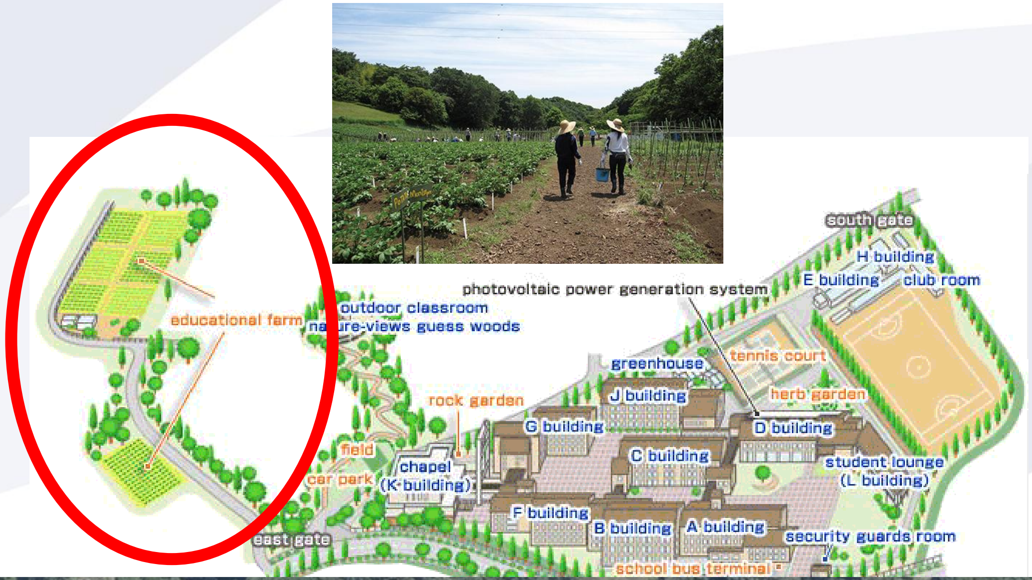
DJI Mavic 3E

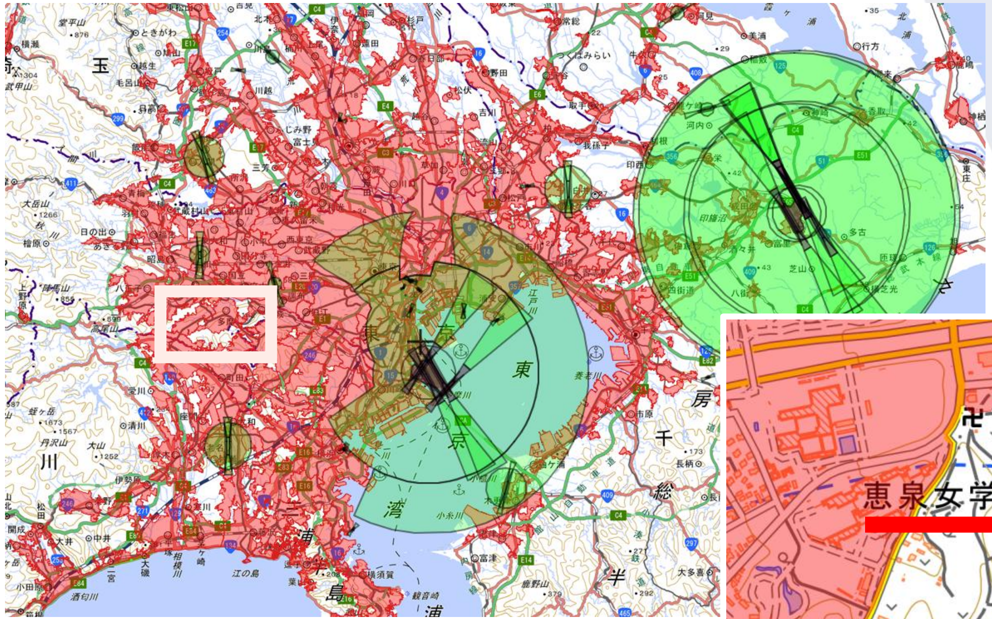
RTK module



# Education Farm at Keisen University

Institute of SCIENCE TOKYO





Basemap: (C) Sentinel-2 cloudless by EOX IT Services GmbH (C) Mapzen

2026~ IEEE Control Systems Society

**TC on Control and Optimization in Food and Agriculture**

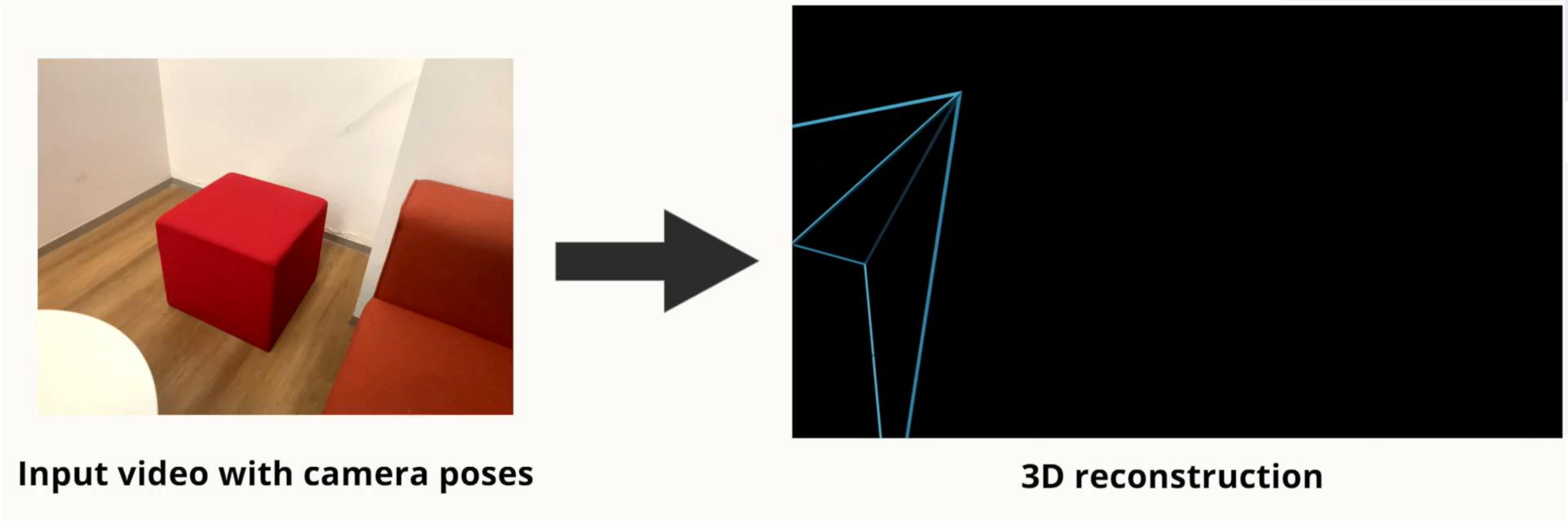

Proposer: Dr. F Fabbene
(CNR, Italy)

Chair: Prof. E Garone
(Université Libre de Bruxelles Belgium)

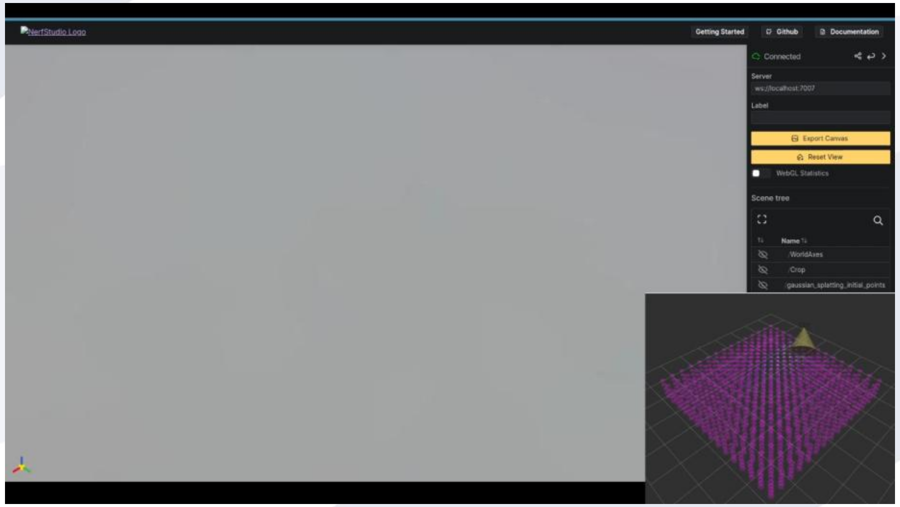
Co-Chair: TH
(Science Tokyo)

# 2. Real-time 3D Mapping Technology

Institute of SCIENCE TOKYO




NeuralRecon [J. Sun et al. CVPR 2021]



Gaussian Splatting
[Kerbl et al. ACM TOG 2023]

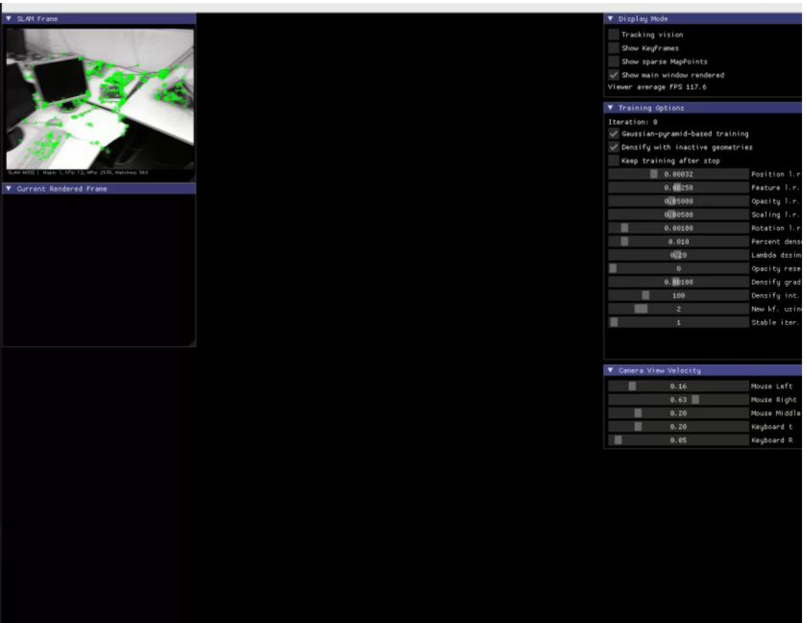
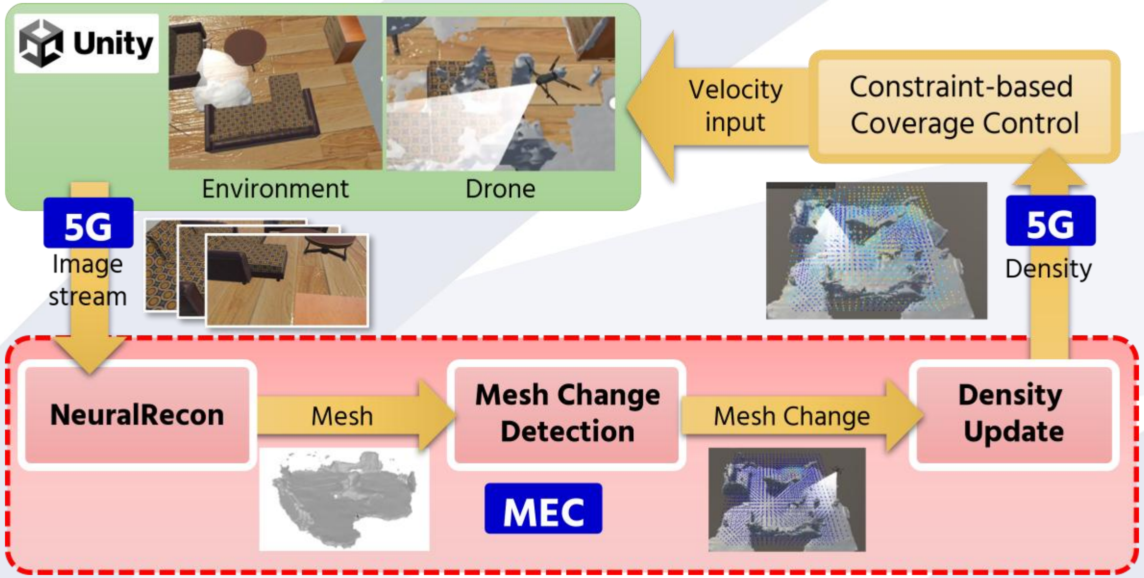
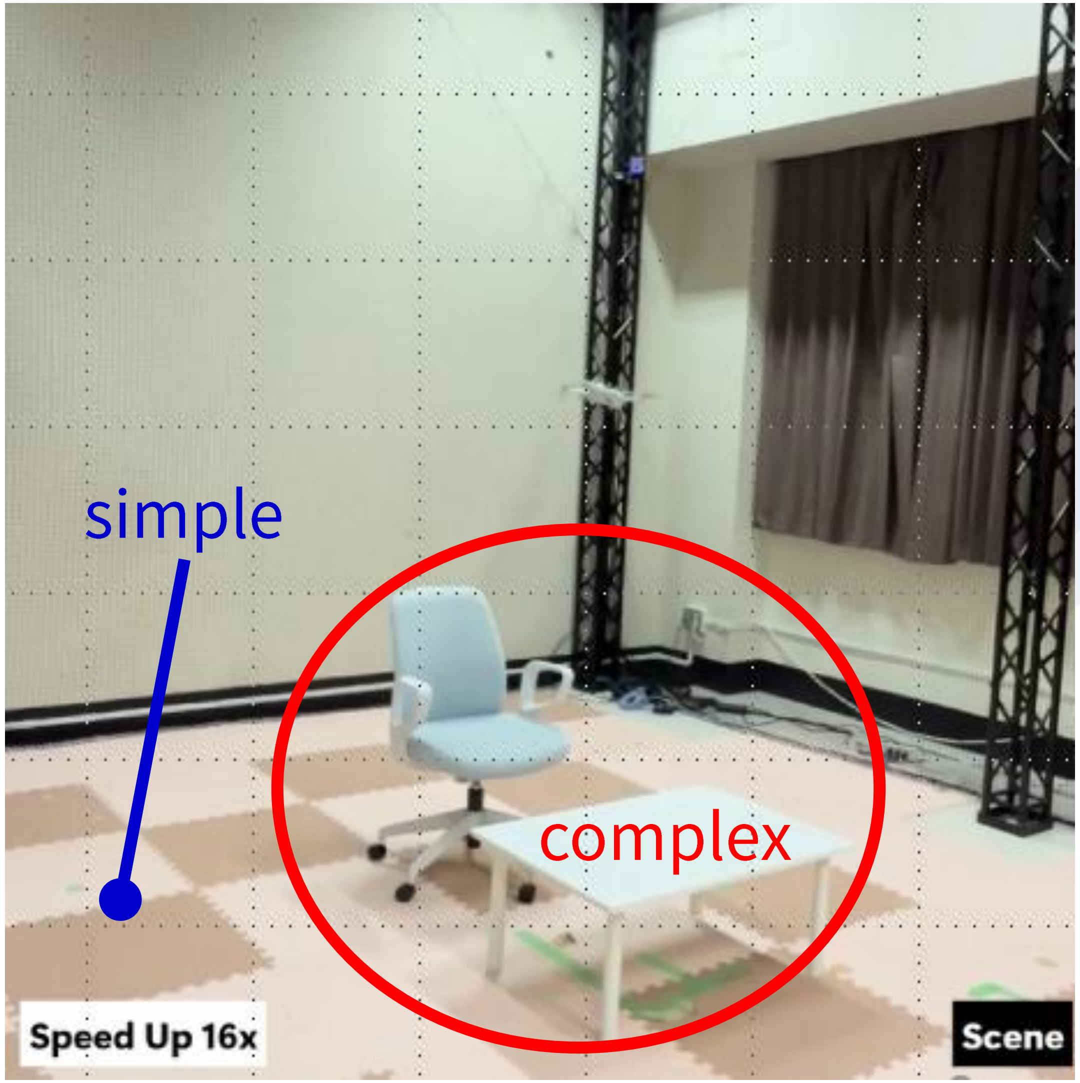


Photo-SLAM
[Huan et al. CVPR 2024]



# Adaptation to Structural Complexity

Institute of SCIENCE TOKYO




structural complexity is uneven!

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

decay rate is even over the field


prior knowledge?

**No, structural complexity is in general unknown in advance!**

# Mesh Change Detection

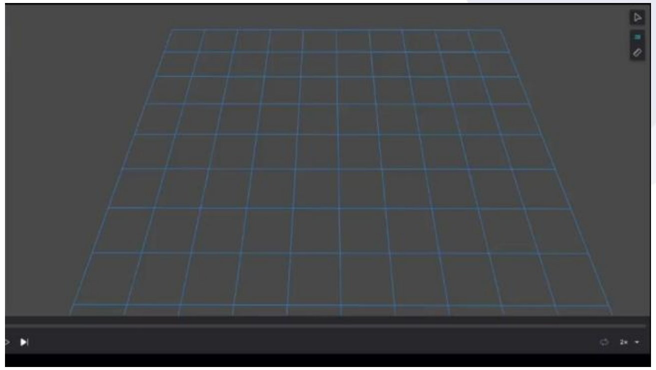
Institute of SCIENCE TOKYO

Iteration-1

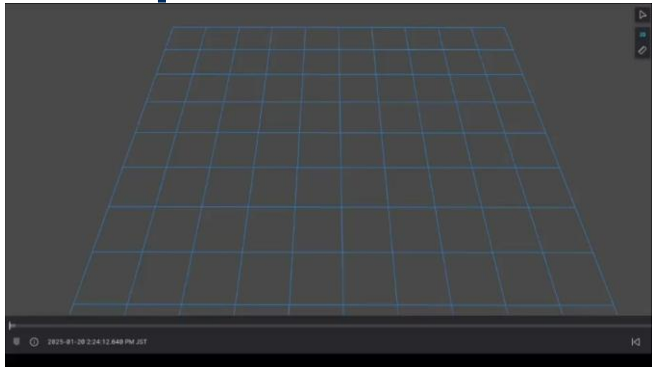
Iteration-2

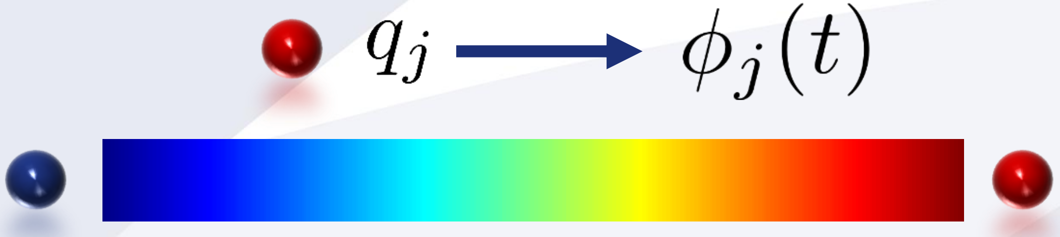
Iteration-n

Mesh Change Extraction



Importance Indices






**Unimportant (Unobserved)**

**Important (Observed)**

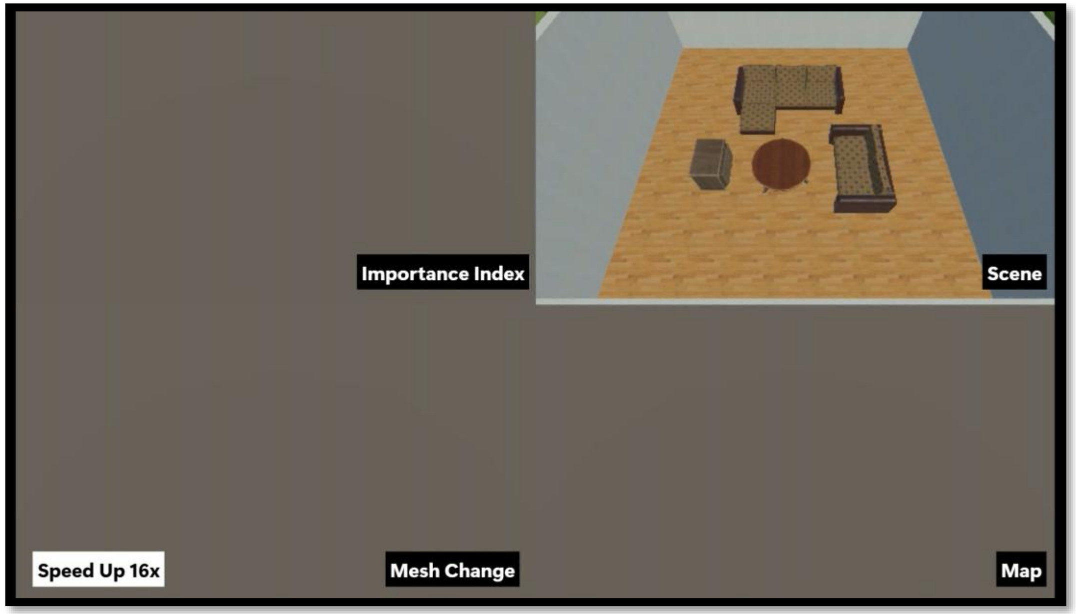
**When a Drone Observes a Target**

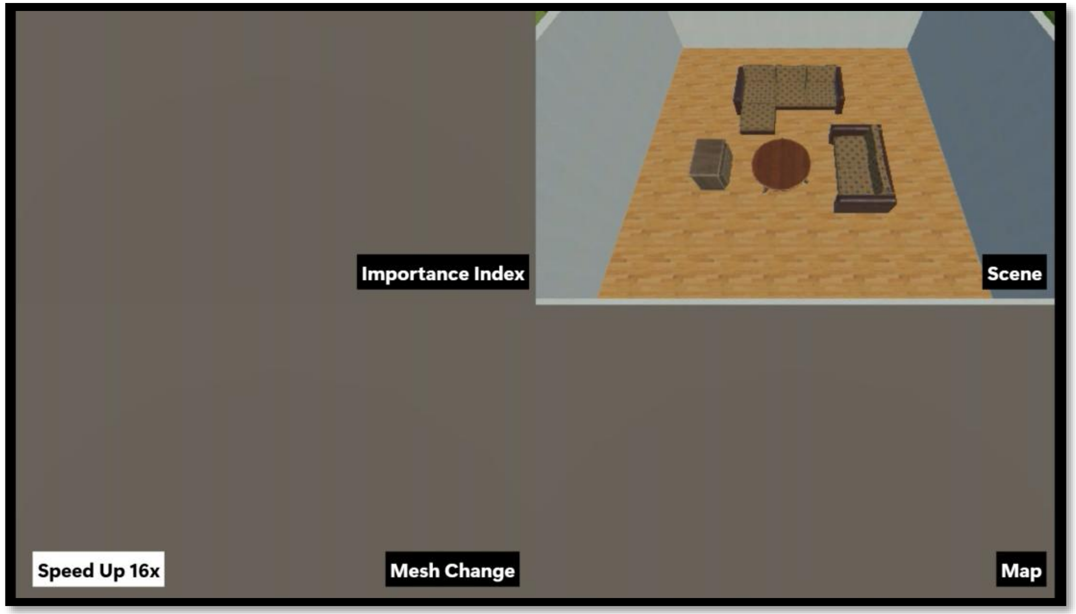
$$\dot{\phi}_j = -\delta \max_{i \in \mathcal{I}} f(p_i, q_j)\phi_j \quad (\delta > 0)$$

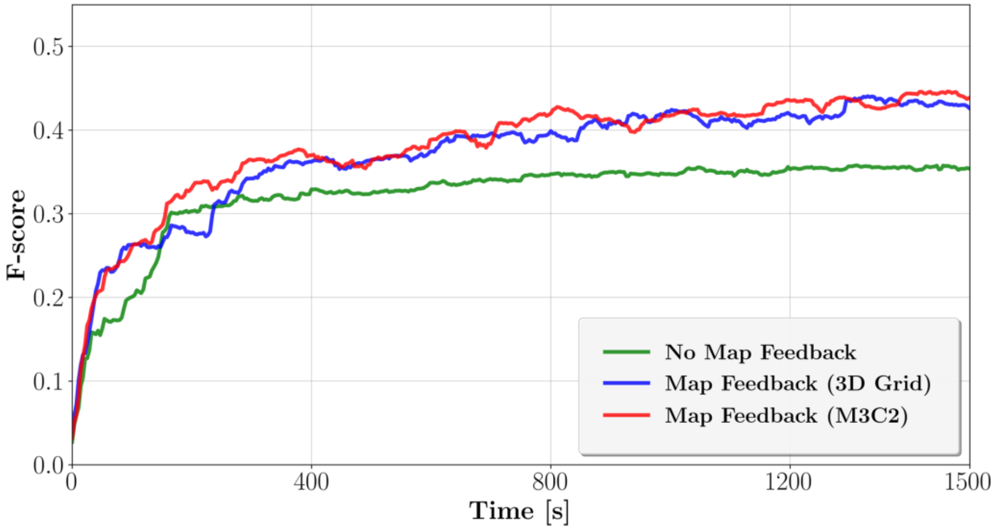
**When Mesh Update Occurs**

$$\phi_j(t^+) = \phi_j(t^-) + \delta_2 h_2(q_j, t) \quad (\delta_2 \geq 0)$$

# Impact of Map Feedback



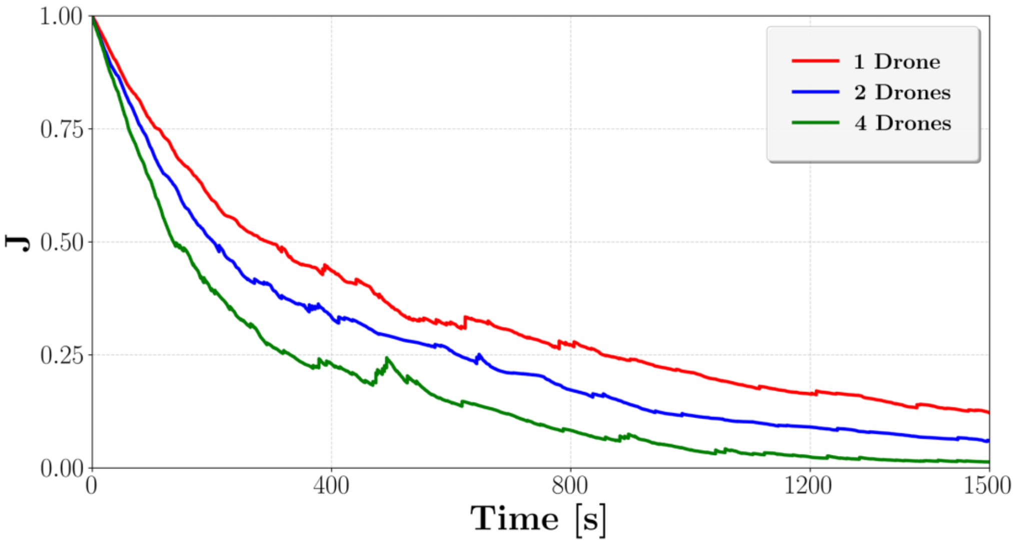




$$\text{F-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{Precision} = \text{mean}_{v \in V}\left(\min_{v^* \in V^*} \|v - v^*\| < \tau\right)$$

$$\text{Recall} = \text{mean}_{v^* \in V^*}\left(\min_{v \in V} \|v - v^*\| < \tau\right)$$



# Comparisons




Ground Truth


Lawn-Mower


[Dan, et.al 2020]

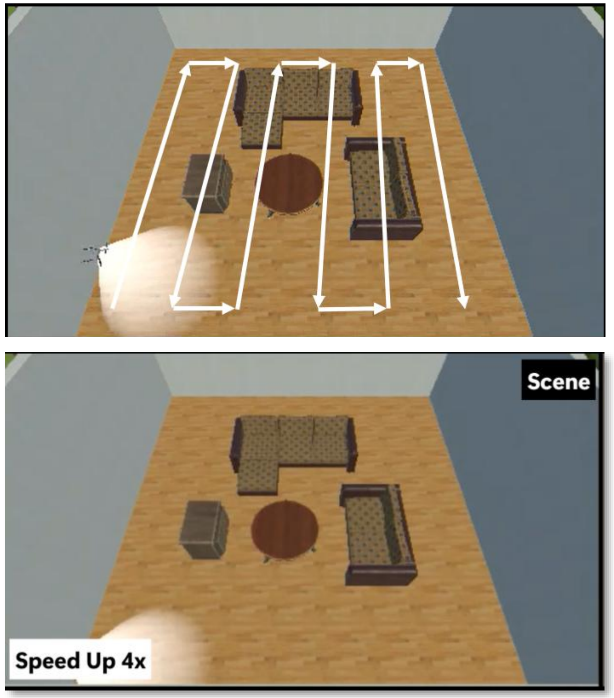

[Shimizu,et.al 2021]


[Lu, et.al 2024]


Ours (No Map Feedback)


Ours (Map Feedback, 3D Grid)

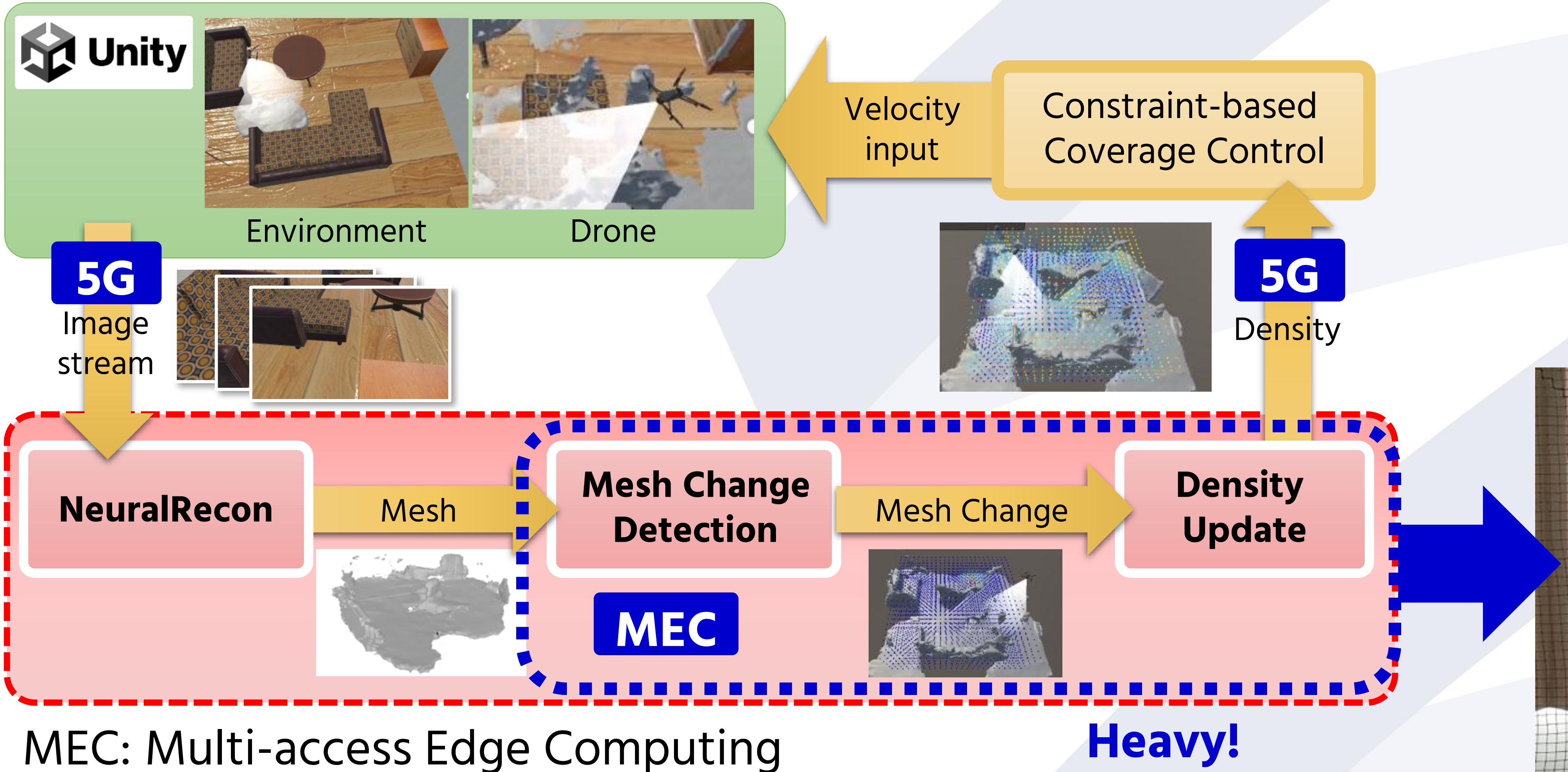

Ours (Map Feedback, M3C2)



Lawn-Mower

# Cyber-Physical Human Systems



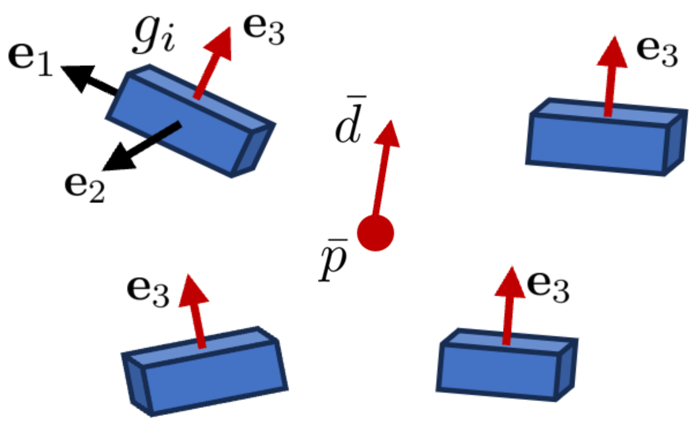



MEC: Multi-access Edge Computing

R. Terunuma, Y. Nakamura, T. Abe, and T. Hatanaka, Stealthy Coverage Control for Human-enabled Real-Time 3D Reconstruction, Proc. 2026 IFAC World Congress, submitted, 2026

# Rigid-body Network and Human

Institute of SCIENCE TOKYO




$$\dot{g}_i^{wc} = g_i^{wc}\hat{V}_i^c$$

$$y_i = R_i \mathbf{e}_3 \text{ (optical axis)}$$

$$g_i^{wc} = \begin{bmatrix} R_i & p_i \\ \mathbf{0}_{1\times 3} & 1 \end{bmatrix} \in SE(3).$$

average position $\bar{p} = \dfrac{1}{n}\sum_{i=1}^{n} p_i$

$$y_{\mathrm{h}} = \begin{bmatrix} \bar{p} \\ \bar{d} \end{bmatrix} \in \mathbb{R}^6$$

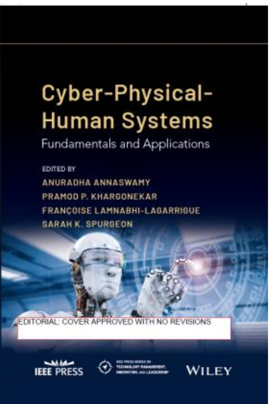
average axis $\bar{d} = \dfrac{\sum_{i=1}^{n} R_i \mathbf{e}_3}{\|\sum_{i=1}^{n} R_i \mathbf{e}_3\|}$

## state-fusion shared control

$$V_i^c = u_{\mathbf{hi}} + u_{\mathbf{ai}}$$

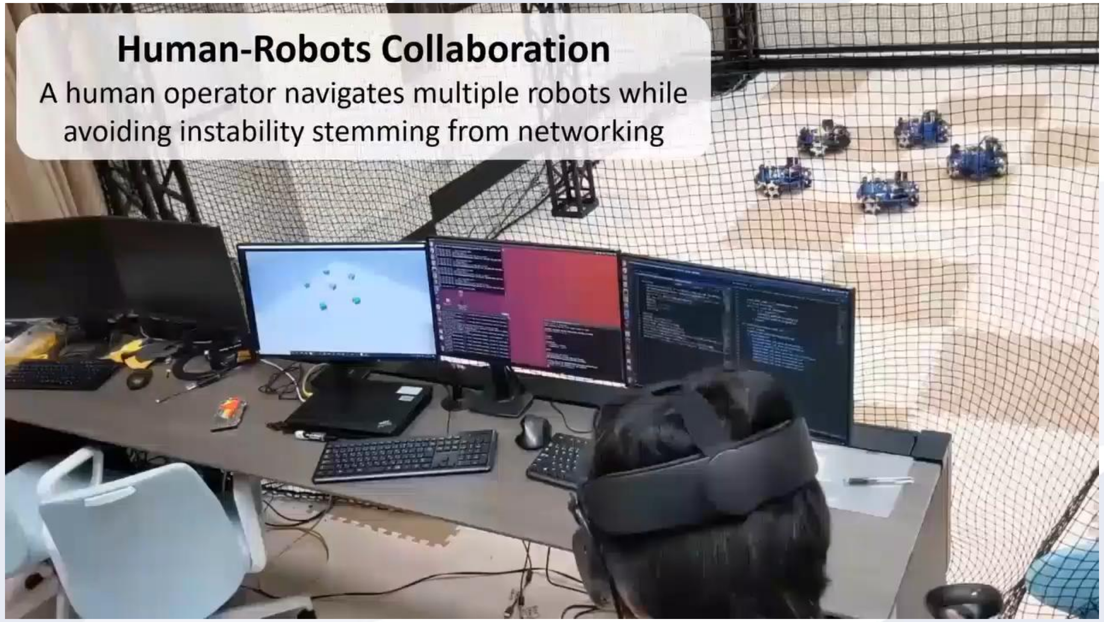
manual control — autonomous coverage control

G. Li et al.(2023). The classification and new trends of sharedcontrol strategies in telerobotic systems: A survey. IEEETrans. Haptics, 16(2), 118–133




## translational control

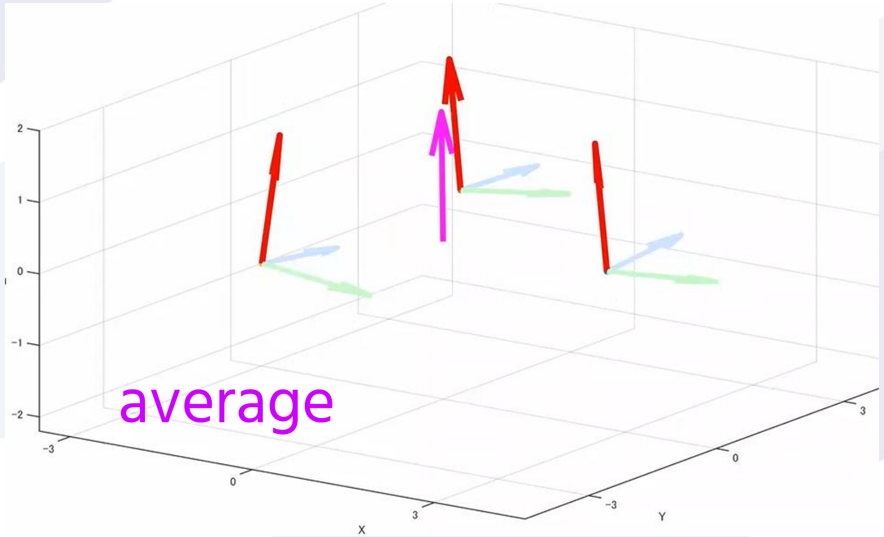
Chapter 14: T. Hatanaka, J. Yamauchi, M. Fujita, and H. Handa, Contemporary Issues and Advances in Human-Robot Collaborations Cyber-Physical-Human Systems: Fundamentals and Applications, A. Annaswamy, P.P. Khargonekar, F. Lamnabhi-Lagarrigue, and S.K. Spurgeon (eds.), Wiley, pp. 365-400, 2023

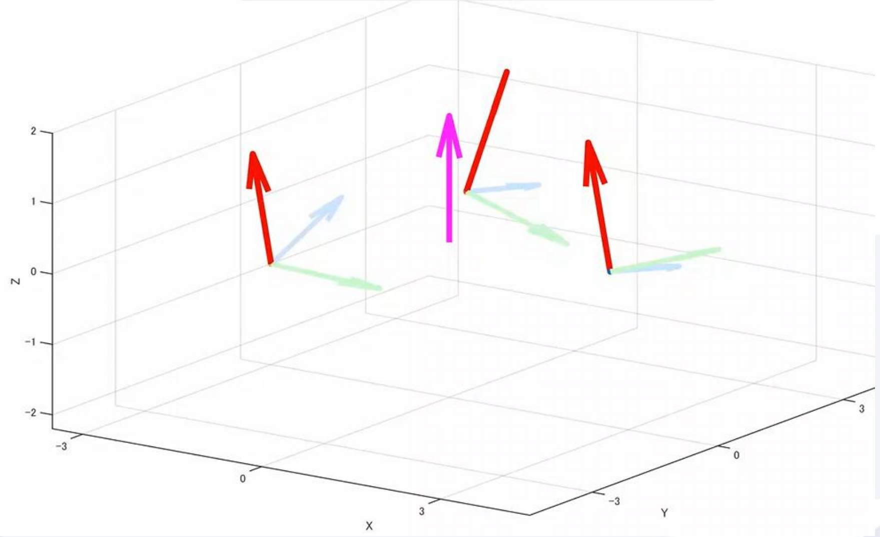


# Stealthy Coverage Control

$$\underline{\dot{y}_{\mathrm{h}} = J(g)(U_{\mathrm{h}} + {\color{red}U_{\mathrm{a}}})}$$

$$g = (g_1^{wc}, \ldots, g_n^{wc}) \quad U_{\mathrm{h}} = (u_{\mathrm{h}1}, \ldots, u_{\mathrm{h}n}) \quad U_{\mathrm{a}} = (u_{\mathrm{a}1}, \ldots, u_{\mathrm{a}n})$$



## Stealthy Control

$$\boldsymbol{\dot{y}_{\mathrm{h}} = J(g)(U_{\mathrm{h}} + \underline{{\color{red}A(g)}}U_{\mathrm{a}}) {\color{red}= J(g)U_{\mathrm{h}}}}$$

(each row) $\in \ker(J(g))$

e.g. $A(g) = I - J^{\dagger}(g)J(g)$

### Stealthy Coverage Control

$$U_{\mathrm{a}}^* = \arg\min_{U_{\mathrm{a}}} \|A(g)U_{\mathrm{a}}\|^2$$

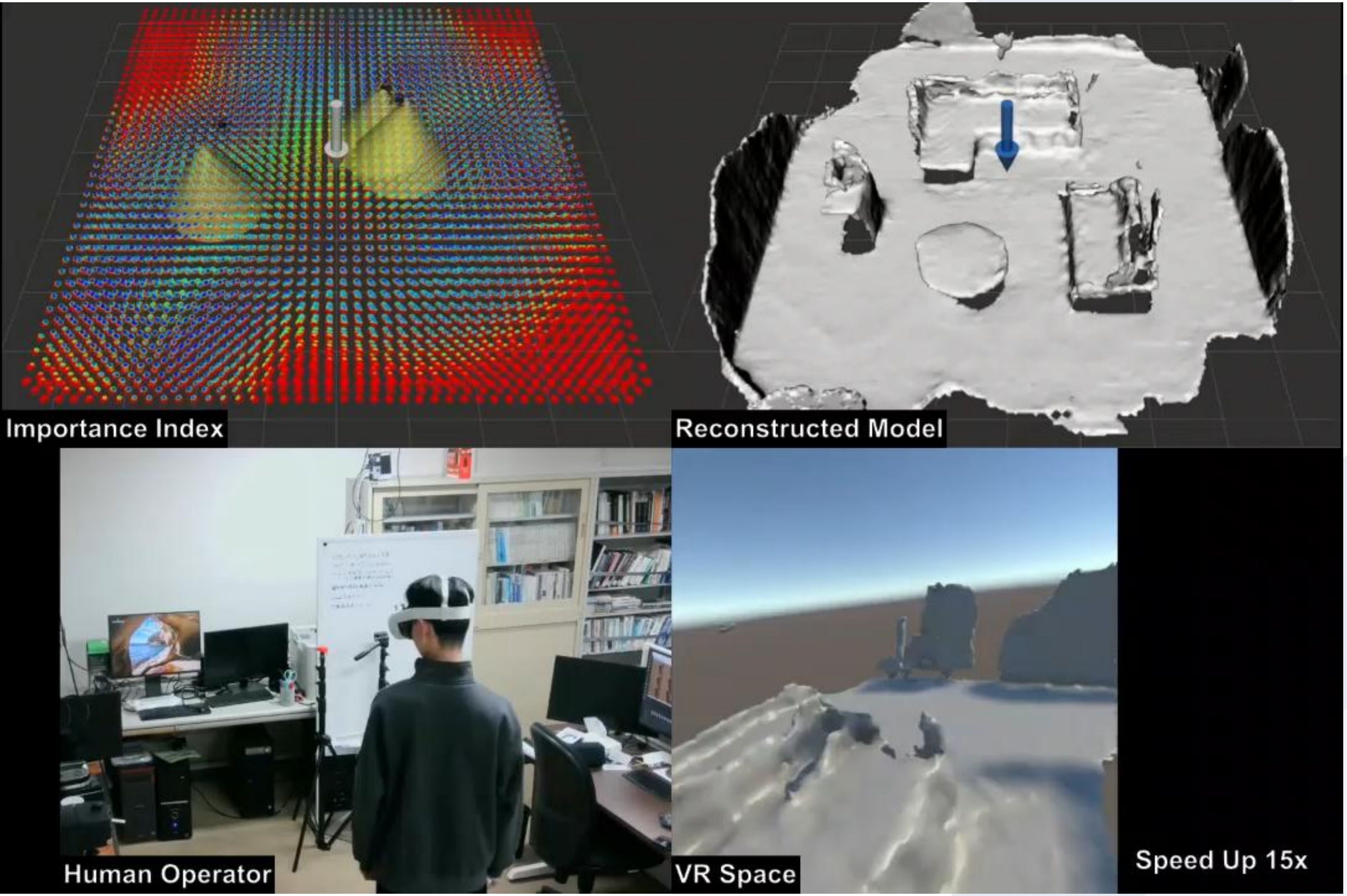
$$\text{s.t.} \quad \frac{\partial b}{\partial g}(U_{\mathrm{h}} + {\color{red}A(g)}U_{\mathrm{a}}) + \alpha(b(g)) \geq 0$$

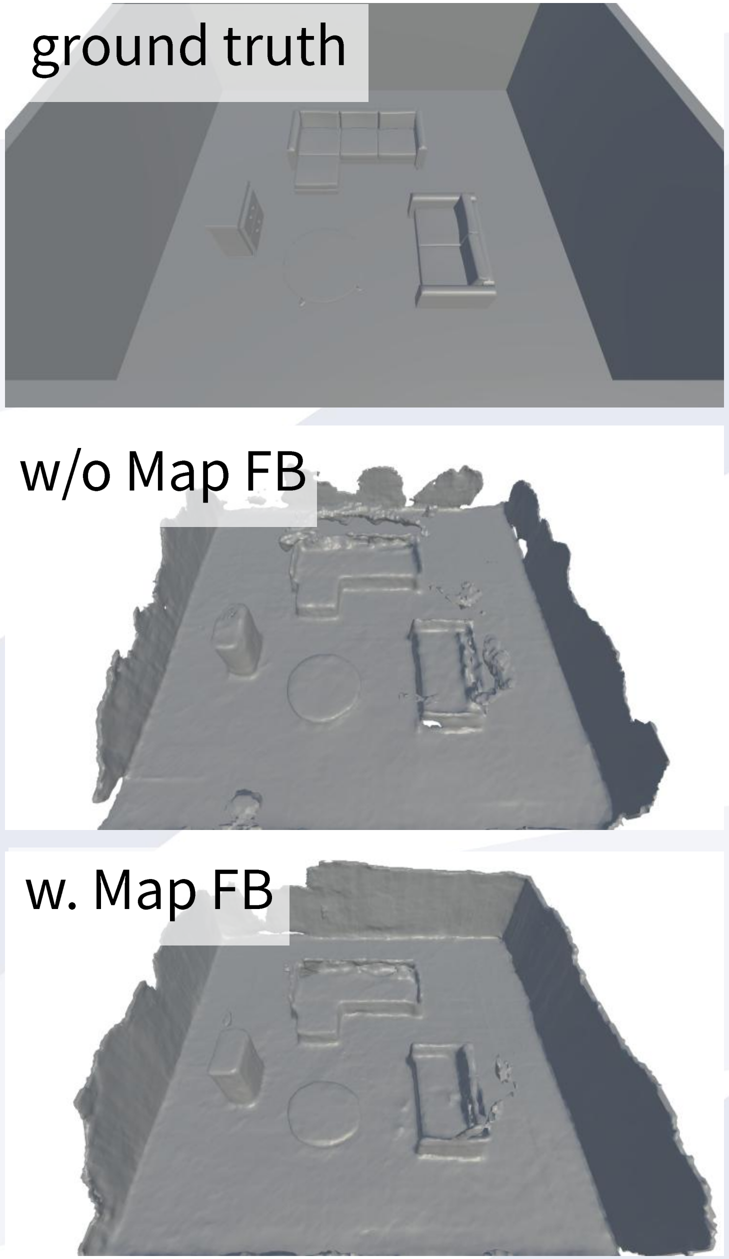
R. Terunuma, Y. Nakamura, T. Abe, and T. Hatanaka, Stealthy Coverage Control for Human-enabled Real-Time 3D Reconstruction, Proc. 2026 IFAC World Congress, submitted, 2026

Institute of SCIENCE TOKYO

# Cyber-Physical Human Systems

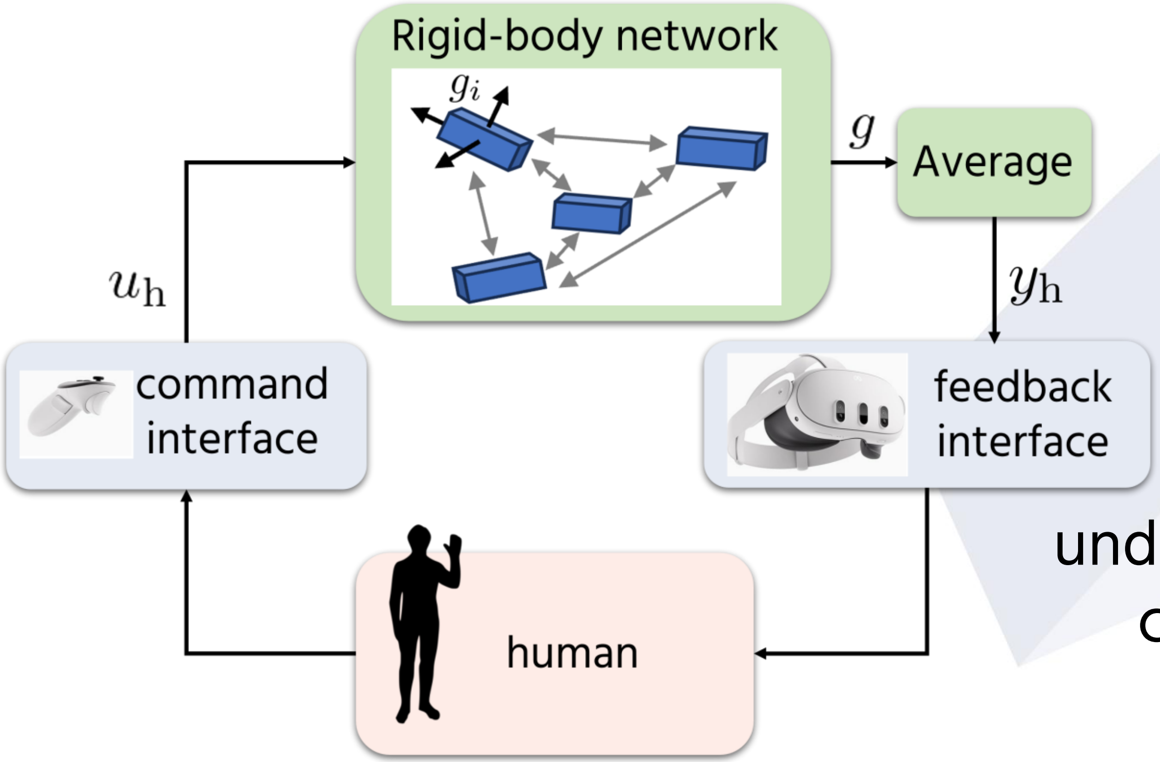
Institute of SCIENCE TOKYO



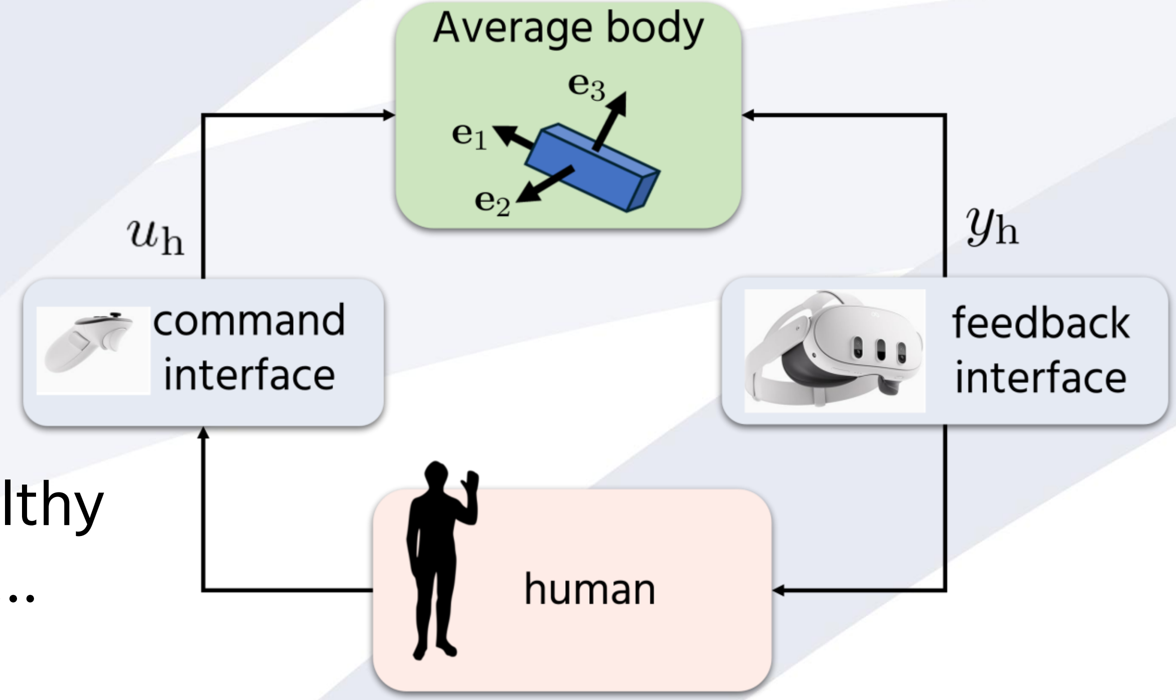



# Stability of Human-in-the-loop System

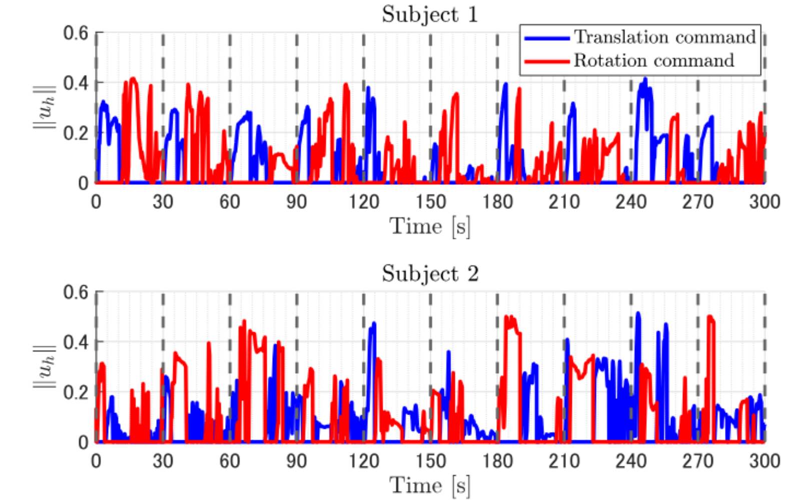


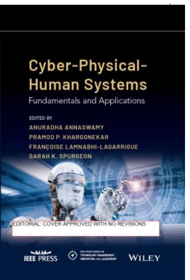



under stealthy control…




**Can we guarantee stability for the simplified human-in-the-loop system?**



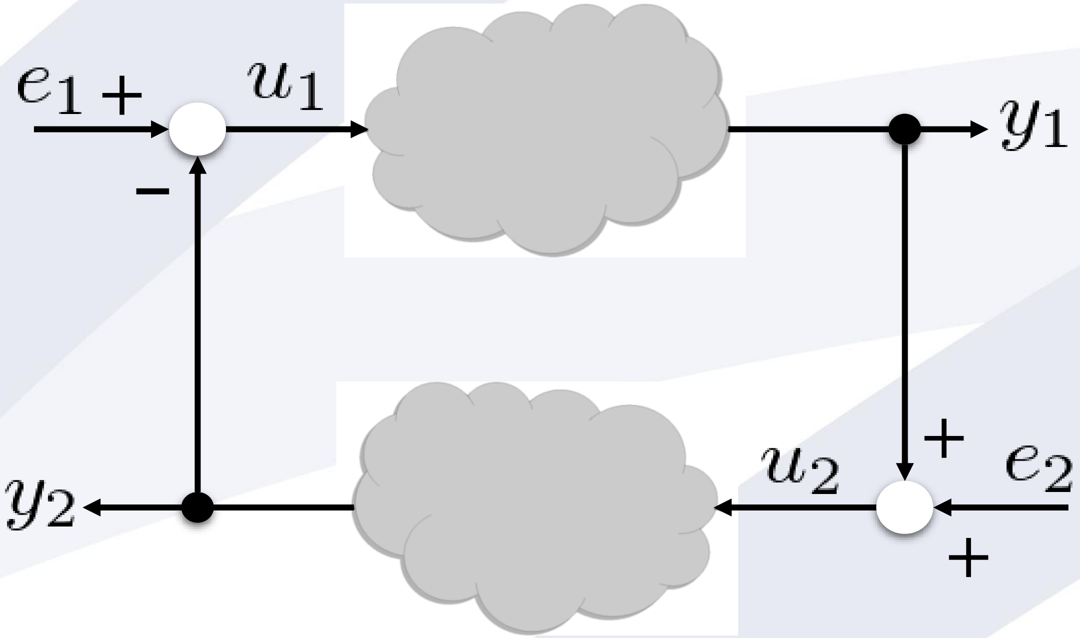

translational control

Chapter 14: T. Hatanaka, J. Yamauchi, M. Fujita, and H. Handa, Contemporary Issues and Advances in Human-Robot Collaborations
Cyber-Physical-Human Systems: Fundamentals and Applications, IEEE-Wiley, pp. 365-400, 2023

# Passivity




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




$$\dot{S}_1 \le y_1^T u_1 = \underline{y_1^T}(e_1 \underline{- y_2})$$

$$\dot{S}_2 \le y_2^T u_2 = \underline{y_2^T}(e_2 + \underline{y_1})$$

$$\dot{S}_1 + \dot{S}_2 \le y_1^T e_1 + y_2^T e_2$$

$$e_1 = e_2 = 0 \quad \Rightarrow \quad \dot{S}_1 + \dot{S}_2 \le 0$$

## Rigid-body Rotational Motion

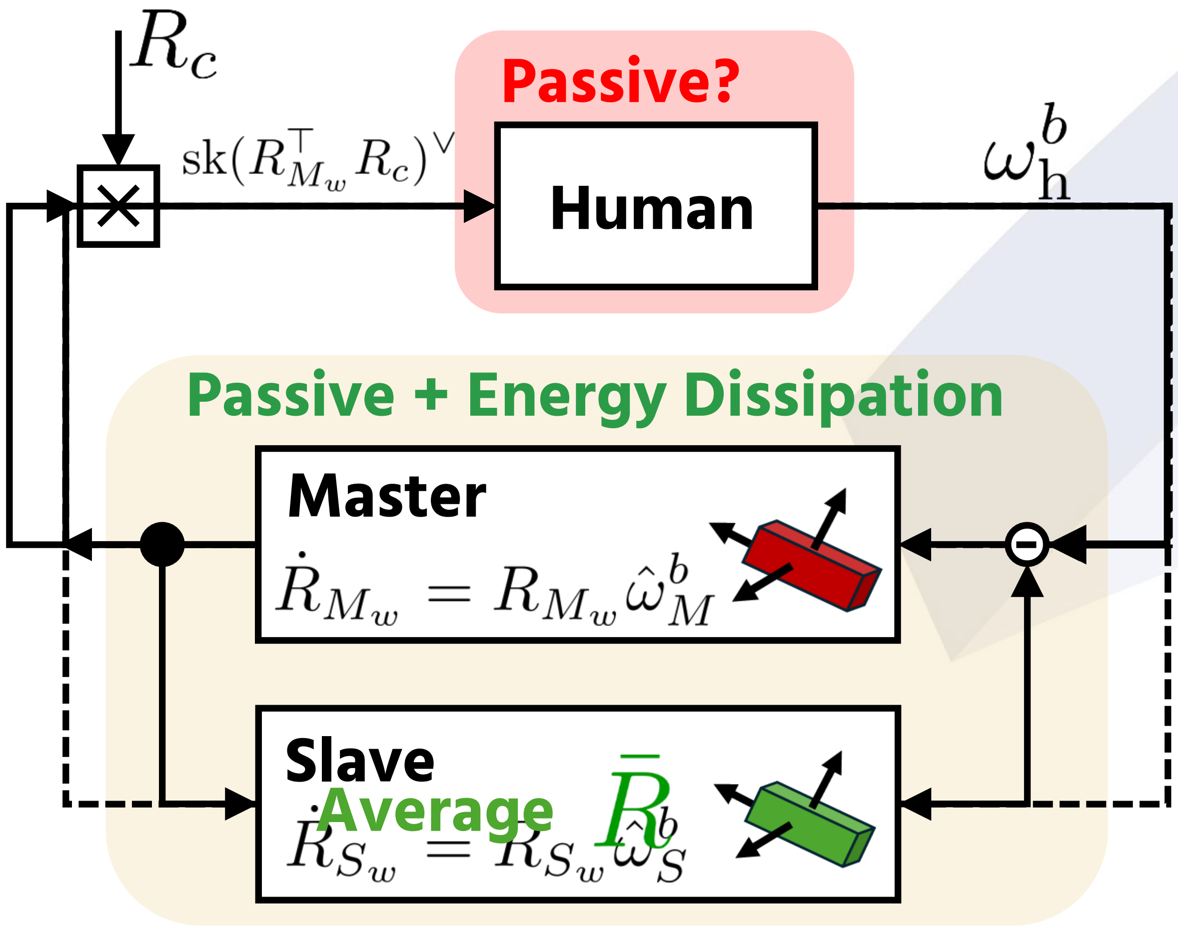
$$\dot{R} = R\hat{\omega}^b \qquad S(R) = \mathrm{tr}(I - R)$$

$$\dot{S} = -\mathrm{tr}(R\hat{\omega}^b) = -\frac{1}{2}\mathrm{tr}(\mathrm{sym}(R)\hat{\omega}^b) - \frac{1}{2}\mathrm{tr}(\mathrm{sk}(R)\hat{\omega}^b)$$

$$= -\frac{1}{2}\mathrm{tr}(\mathrm{sk}(R)\hat{\omega}^b) = (\mathrm{sk}(R)^\vee)^T\omega^b$$

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

# Passivity-based Design

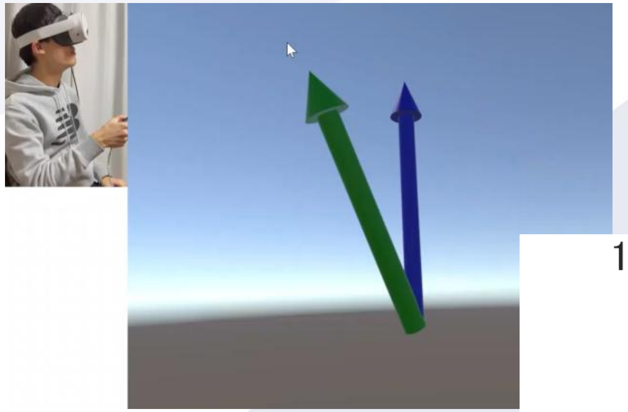



Thm: $\lim_{t\to\infty} \|\bar{R} - R_c\|_F = 0$ under

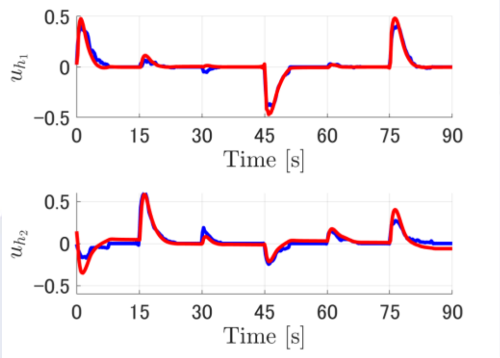
- **human passivity**

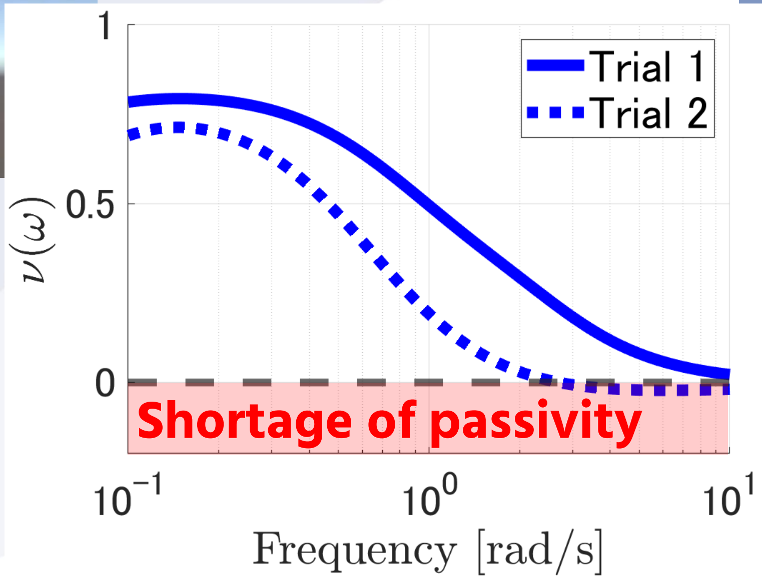
$$\dot{S}_\mathrm{h} \leq \{\mathrm{sk}(R_{M_w}^\top R_c)^\vee\}^\top \omega_\mathrm{h}^b$$

- bounded states of human



human modeling

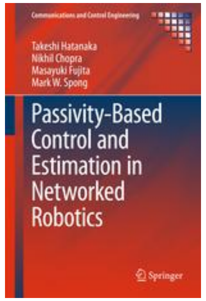



motion synchronization law

$$\omega_M^b = \mathrm{sk}(R_{M_w}^\top R_{S_w})^\vee + \omega_\mathrm{h}^b$$

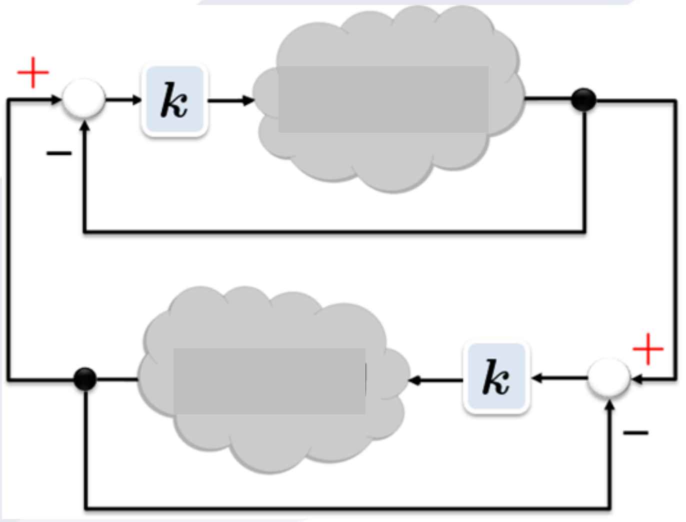
$$\omega_S^b = \mathrm{sk}(R_{S_w}^\top R_{M_w})^\vee$$



# Passivity Shortage

Institute of SCIENCE TOKYO


$$\dot{S} \le y^T(\tau)u(\tau) + \epsilon\|u(\tau)\|^2$$




$$\dot{S}_1 \le y_1^T u_1 + \epsilon\|u_1\|^2$$

$$\dot{S}_2 \le y_2^T u_2 + \epsilon\|u_2\|^2$$

<u>consensus algorithm:</u>

$$u_1 = k(y_2 - y_1)$$
$$u_2 = k(y_1 - y_2)$$

$$\dot{S}_1 + \dot{S}_2 \le k y_1^T(y_2 - y_1) + k y_2^T(y_1 - y_2) + 2\epsilon k^2\|y_1 - y_2\|^2$$

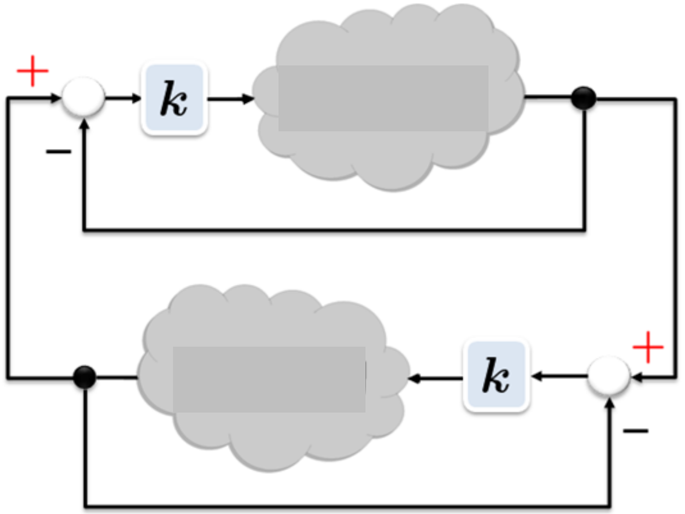
$$= -k\|y_1 - y_2\|^2 + 2\epsilon k^2\|y_1 - y_2\|^2 = -k(\underline{1 - 2\epsilon k})\|y_1 - y_2\|^2$$

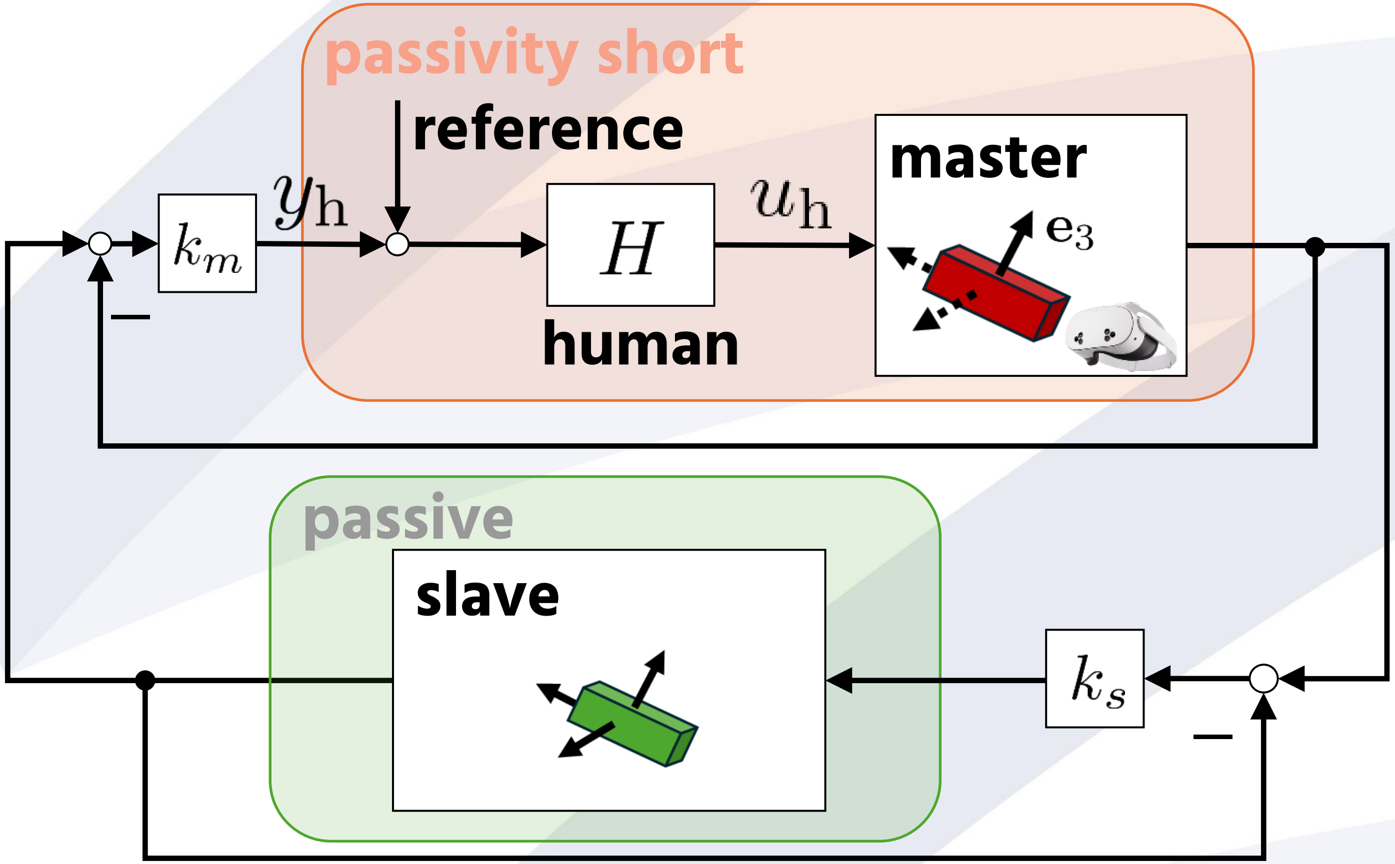
weak gain

$$k \le 1/(2\epsilon) \longrightarrow \dot{S}_1 + \dot{S}_2 \le 0$$

Z. Qu and M.A. Simaan, Modularized Design for Cooperative Control and Plug-and-Play Operation of Networked Heterogeneous Systems; Automatica, Vol. 50, No. 9, pp. 2405-2414 (2014)

# Passivity-shortage-based Design




R. Terunuma, Y. Nakamura, T. Abe, and T. Hatanaka, Passivity-based Semi-autonomous Navigation for Rigid Body Networks: Stability and Human Passivity Analysis 6th IFAC Workshop on Cyber-Physical Human Systems, under preparation, 2026

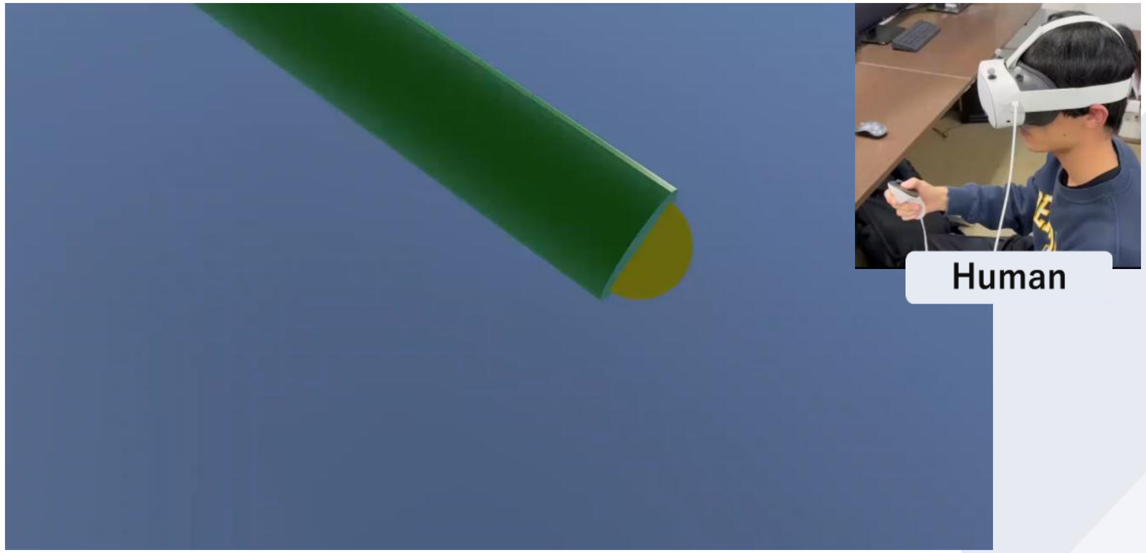
Thm: $\lim_{t\to\infty} \|y - r_c\| = 0$ under

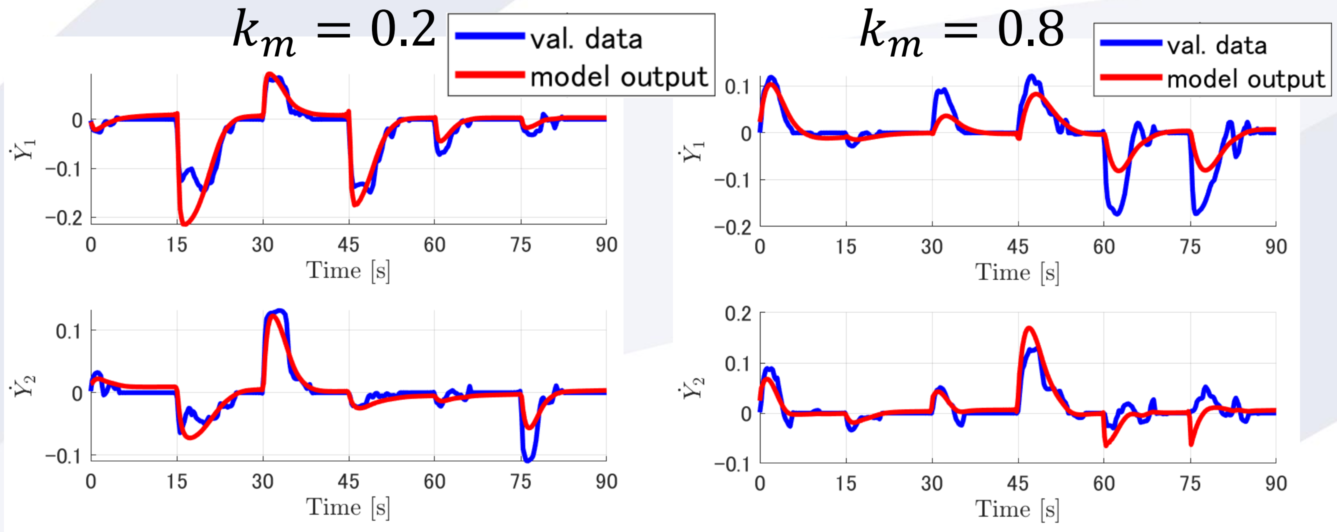
- **human passivity short with $\nu > -1$**

$$\dot{S}_{\rm h} \leq (r^b_{c\perp} - y^b_{{\rm h}\perp})^\top (r^b_{\perp} - r^b_{c\perp}) - \nu \|r^b_{c\perp} - y^b_{{\rm h}\perp}\|^2$$

# Human Modeling

Institute of SCIENCE TOKYO

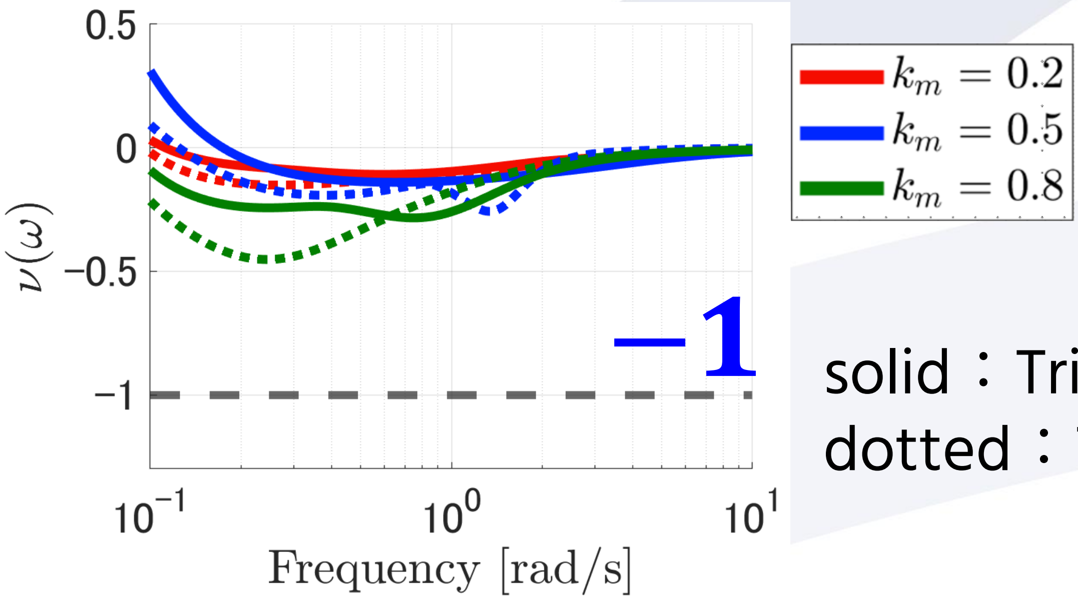



reference randomly jumps at every 15s

Fit ratios

| $k_m$ | Training data | Test data |
|---|---|---|
| 0.2 | 75.25% | 60.58% |
| 0.5 | 66.44% | 43.17% |
| 0.8 | 60.23% | 52.70% |




**master**

**slave**

solid：Trial 1

dotted：Trial 2

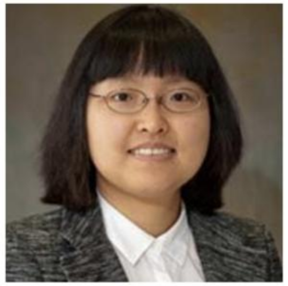
# IFAC CPHS 2026 in LA


Invited Session Submission: May 6, 2026
**Paper/Abstract Submission: May 20, 2026**
Decision Notification: Sep 15, 2026
Final Submission: Oct 15, 2026
Conference Date: December 11-12th, 2026

Ketan Savla
Co-General Chair
ksavla@usc.edu
University of Southern California, USA

Takeshi Hatanaka
Co-General Chair
hatanaka@sc.e.titech.ac.jp
Institute of Science Tokyo, Japan

Jeff Shamma
Program Chair
jshamma@illinois.edu
University of Illinois Urbana-Champaign, USA



Yue Wang
Program Co-chair
yue6@g.clemson.edu
Clemson University, USA

Masaki Inoue
Program Co-Chair
minoue@appi.keio.ac.jp
Keio University, Japan

Miwa Ueki
Vice-chair for Industry
ueki.miwa@fujitsu.com
Fujitsu, Japan

Tomohisa Hayakawa
Publication Chair
hayakawa@sc.e.titech.ac.jp
Institute of Science Tokyo, Japan

Ruolin Li
Publicity Chair
ruolinl@usc.edu
University of Southern California, USA

Jonathan Realmuto
Local Arrangements Chair
jrealmut@ucr.edu
University of California Riverside, USA

Solmaz Kia
Registration Chair
solmaz@uci.edu
University of California Irvine, USA

Angela Fontan
Invited Sessions Chair
angfon@kth.se
KTH Royal Institute of Technology, Sweden

Katherine Flanigan
Outreach Chair
kflaniga@andrew.cmu.edu
Carnegie Mellon University, USA

Petros Ioannou
Finance Chair
ioannou@usc.edu
University of Southern California, USA

Anthony Rossiter
IFAC Conference Board Liasion
The University of Sheffield, UK

# Summary

Institute of SCIENCE TOKYO