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EURECOM
Sophia Antipolis

Robot-Augmented Sensing and Localization (and connectivity) for 6G Networks

6GWFF

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Robot-augmented networks: Connectivity

Relay-based connectivity

Hot-spots, sport events, flashcrowds, disaster recovery,..

D2D connectivity

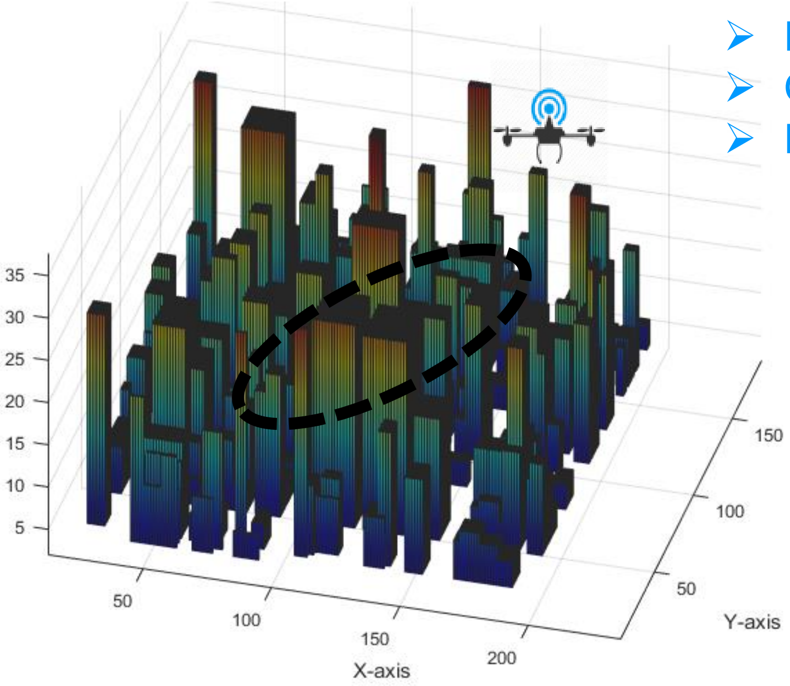
car2car connectivity, mesh connectivity, battlefield connectivity,..

Non delay sensitive connectivity

IoT data harvesting, smart city, agriculture, caching,..

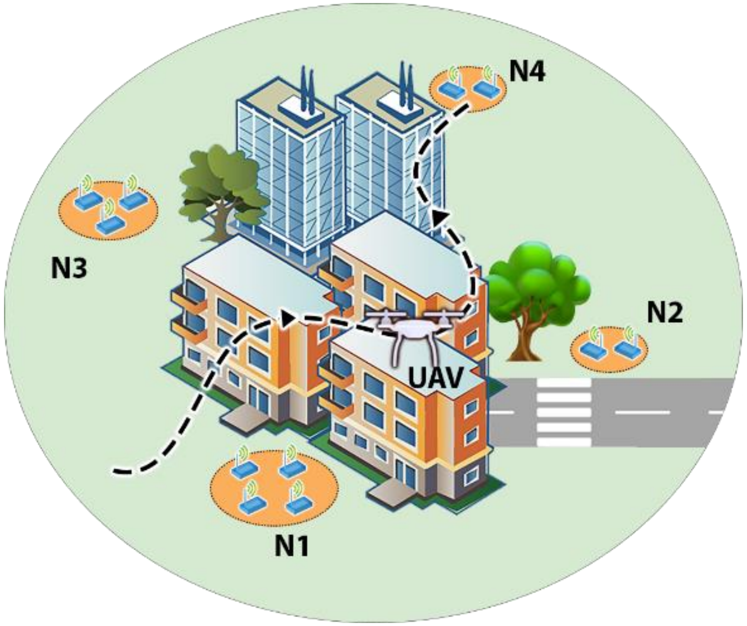
Robot-augmented RF Sensing & Localization

- Injecting a robot in the network for sensing: Why?
  - Robot-borne (UAV, cars,..) enrich sensing data space
  - Opportunity to optimize path to design meaningful data
  - Dealing with Non Line of Sight challenge



Robot-aided mapping

Radio map, 3D Map reconstruction,
Outdoor, indoor (factory setting)

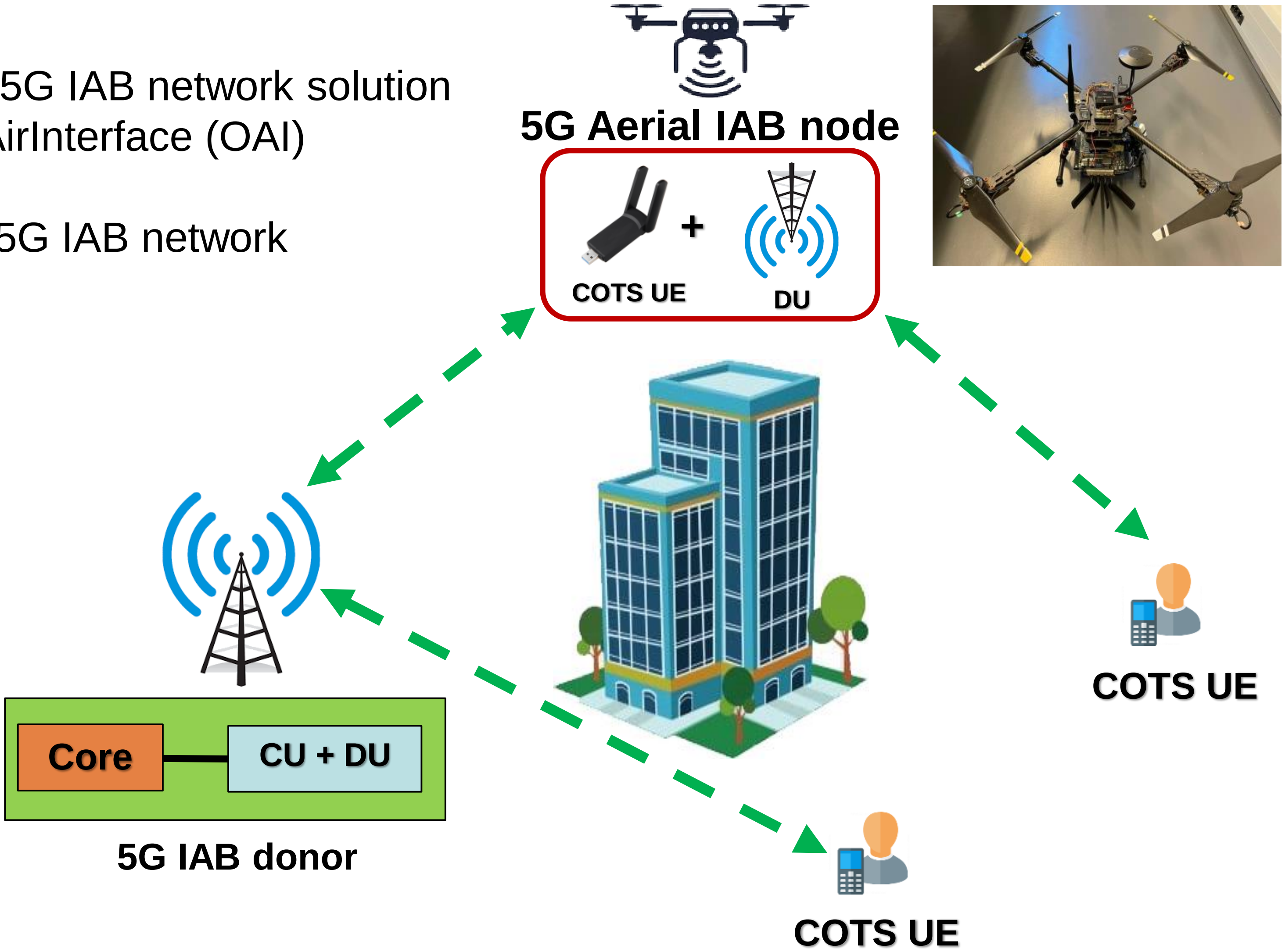


Robot-aided localization

D. Gesbert, O. Esrafilian, J. Chen, R. Gangula, U. Mitra, "UAV-aided RF Mapping for Sensing and Connectivity in Wireless Networks", IEEE Communications Magazine, 2022.

Connectivity: Aerial Integrated Access and Backhaul (IAB)

- First end-to-end 5G IAB network solution based on OpenAirInterface (OAI)
- First UAV-aided 5G IAB network demonstration



Mundlamuri, R., Esrafilian, O., Gangula, R., Kharade, R., Roux, C., Kaltenberger, F., ... & Gesbert, D. (2023). Integrated Access and Backhaul in 5G with Aerial Distributed Unit using OpenAirInterface. *arXiv preprint arXiv:2305.05983*.

UAV-aided Data Harvesting based on learning

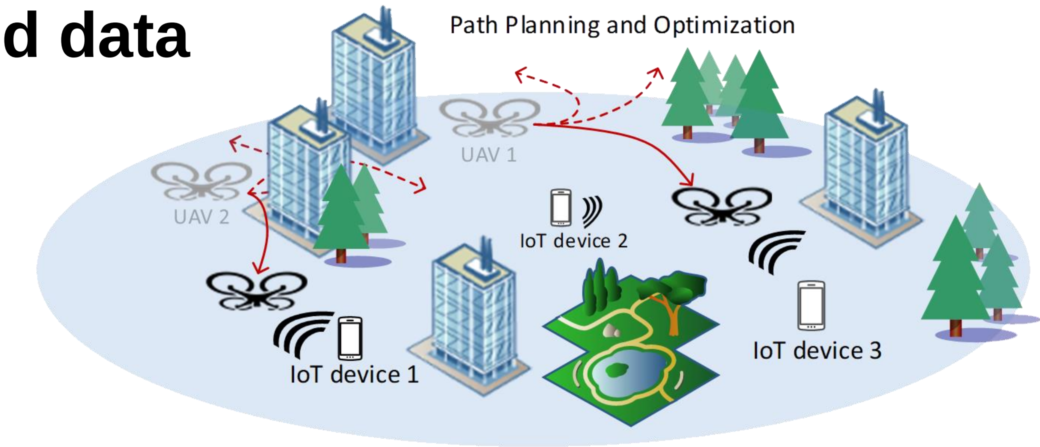
- **Maximizing total collected data**

$$\max_{\chi} \sum_{n=1}^{N}\sum_{m=1}^{M}\sum_{k=1}^{K} C(\mathbf{u}_k, \mathbf{v}_m[\boldsymbol{n}])$$

$$\text{s.t.} \quad \text{Consumed energy} \leq \text{B}$$

$$\mathbf{v}_m[\mathbf{1}] = \mathbf{v}_s$$

$$\mathbf{v}_m[N] = \mathbf{v}_t$$



Transmit power

$$C(\mathbf{u}_k, \mathbf{v}_n) = \frac{1}{K}\log_2\left(1 + \frac{P\ 10^{0.1*g_{k,n}}}{\sigma^2}\right)$$

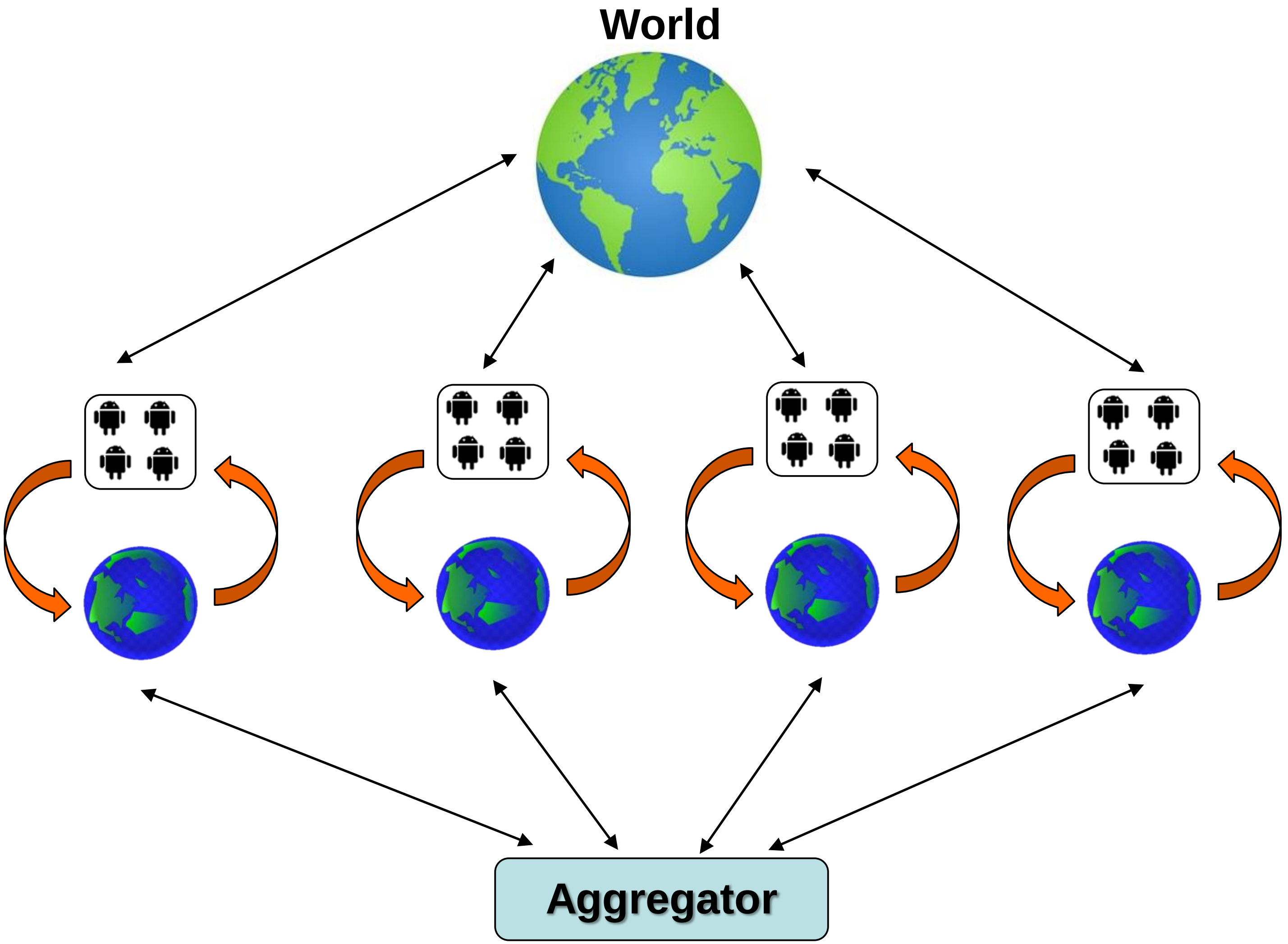
Received noise power

Localization
+
Learning
+
Classification

$$g_{k,m}[n] = \begin{cases} \psi_\theta\big(\mathbf{u}_k, \mathbf{v}_m[\boldsymbol{n}], \omega_{k,m}[n] = LoS\big) + \xi_{LoS}\ , & if\ LoS \\ \psi_\theta\big(\mathbf{u}_k, \mathbf{v}_m[\boldsymbol{n}], \omega_{k,m}[n] = NLoS\big) + \ \xi_{NLoS}\ , & if\ NLoS \end{cases} \ , \ \xi_\omega \sim \mathcal{N}(0, \sigma_\omega^2)$$

$$\boldsymbol{u}_k = \{\boldsymbol{\mathcal{U}}_{known}, \boldsymbol{\mathcal{U}}_{unknown}\}, \quad \text{unknown channel} \left\{\psi_\theta\big(\mathbf{u}_k, \mathbf{v}_m[\boldsymbol{n}], \omega_{k,m}[n]\big); \omega_{k,m}[n] \in \{\text{LoS, NLoS}\}\right\}$$

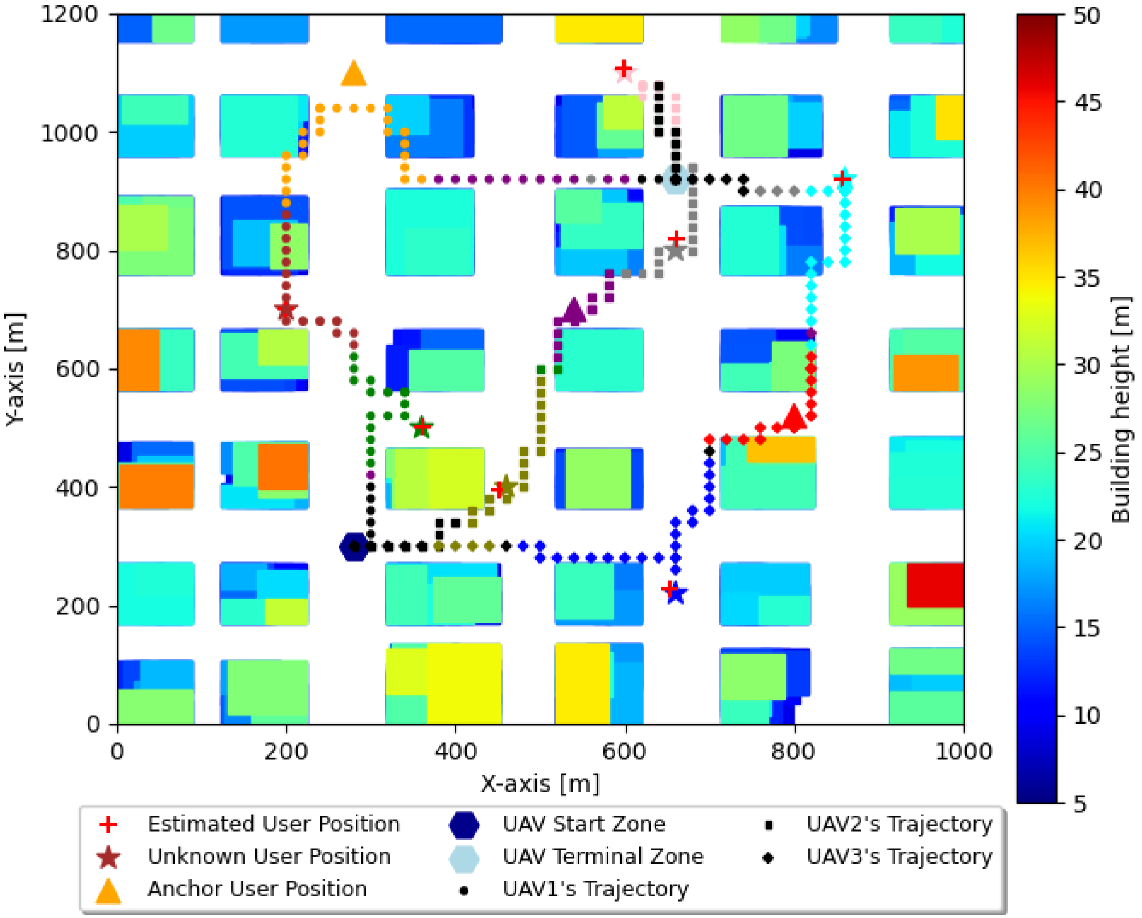
Digital Twin-aided Federated Multi-agent DRL



J. Chen, O. Esrafilian, H. Bayerlein, D. Gesbert, and M. Caccamo, "Model-aided Federated Reinforcement Learning for Multi-UAV Trajectory Planning in IoT Networks", Submitted to IEEE Globecom, 2023.

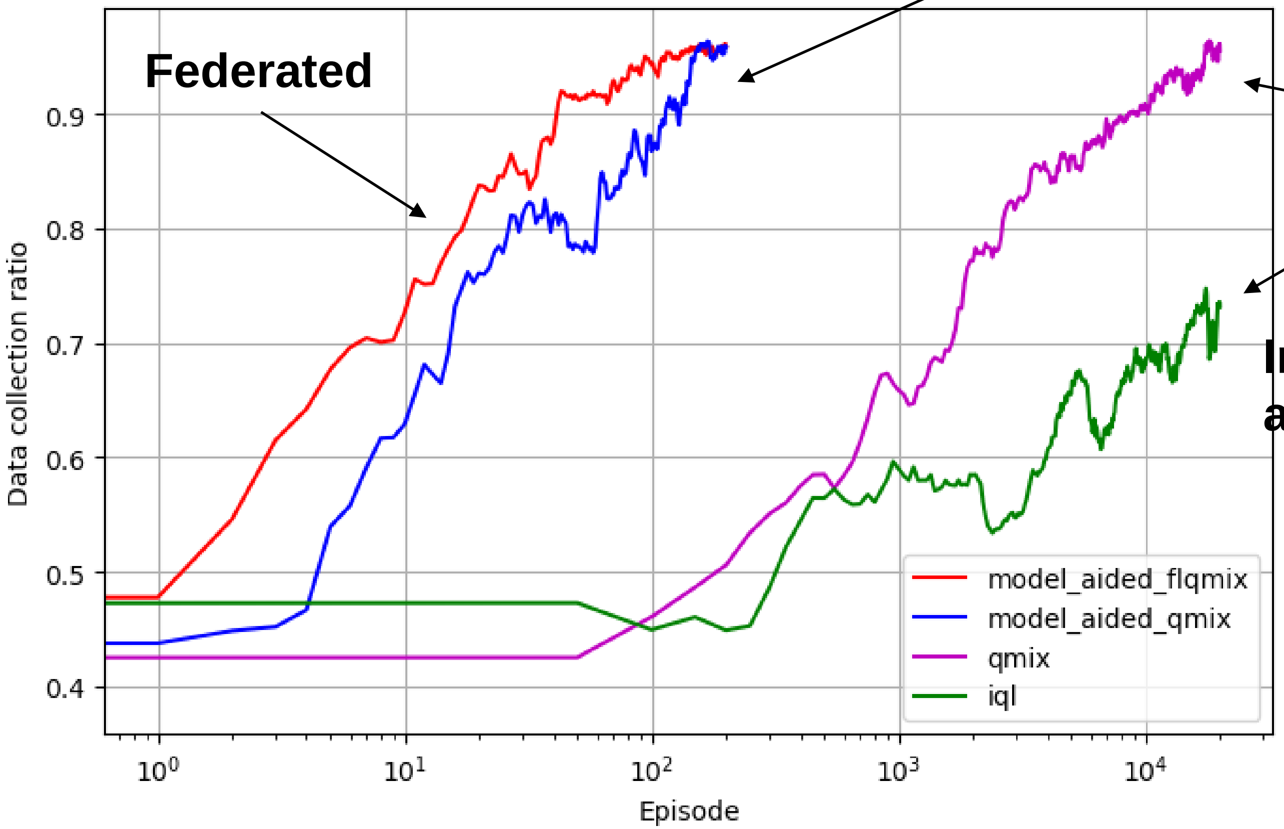
Simulations

M=3 UAVs, UAV Altitude: 60 m, 3 Anchor Nodes



Simulations

M=3 UAVs, UAV Altitude: 60 m, 3 Anchor Nodes



Digital twin-aided

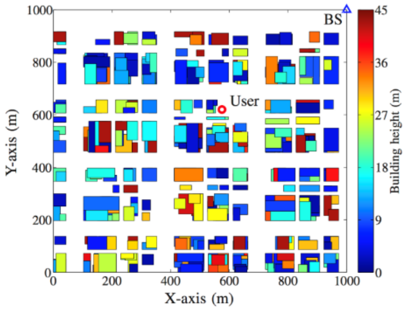
Federated

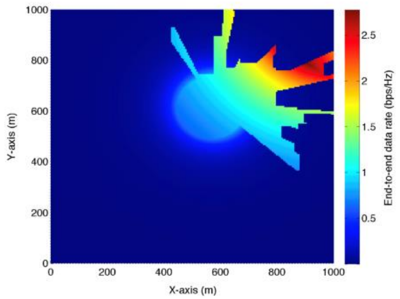
Model less

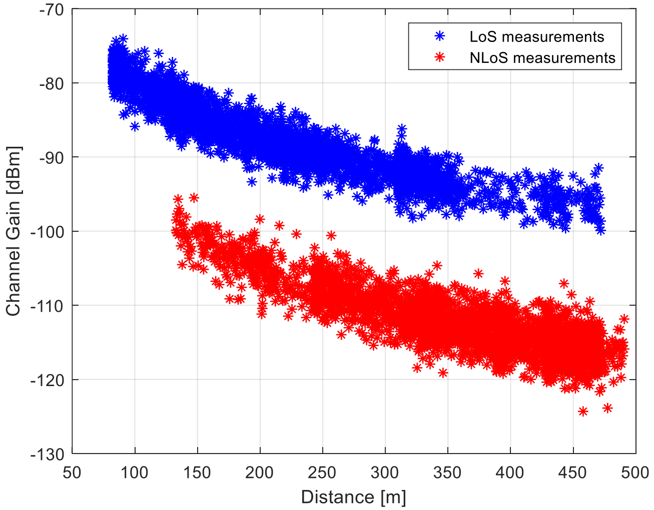
Independent agents

Sensing & mapping via channel classification

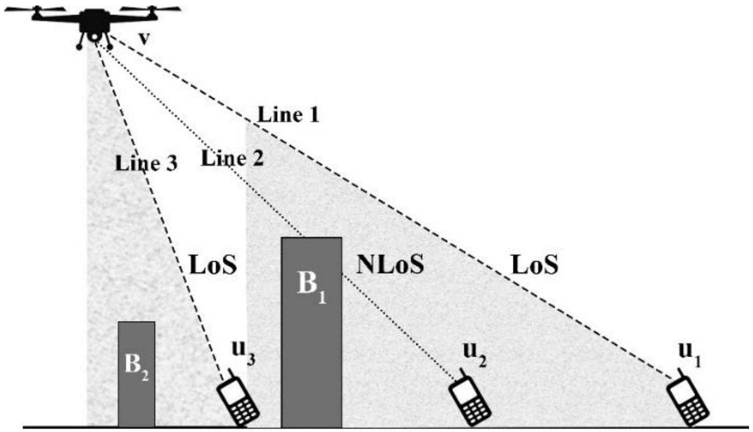
- Supervised: Using the 3D map
- Unsupervised: Using clustering (map reconstruction is implicit)







LoS/NLoS



Av. RX power

Fixed offset

shadowing

$$\gamma_s = \frac{\beta_s}{d^{\alpha_s}} \varepsilon_s$$

S: fading class (1,2,3..)

distance

Path loss exponent

RSSI-based UE Localization

- **Problem formulation:**

$$\min_{\mathbf{u}_k,\boldsymbol{\theta},f(.)} \sum_{n,k} \left\| \gamma_{n,k} - f(\mathbf{v}_n, \mathbf{u}_k, \boldsymbol{\theta}) \right\|^2$$

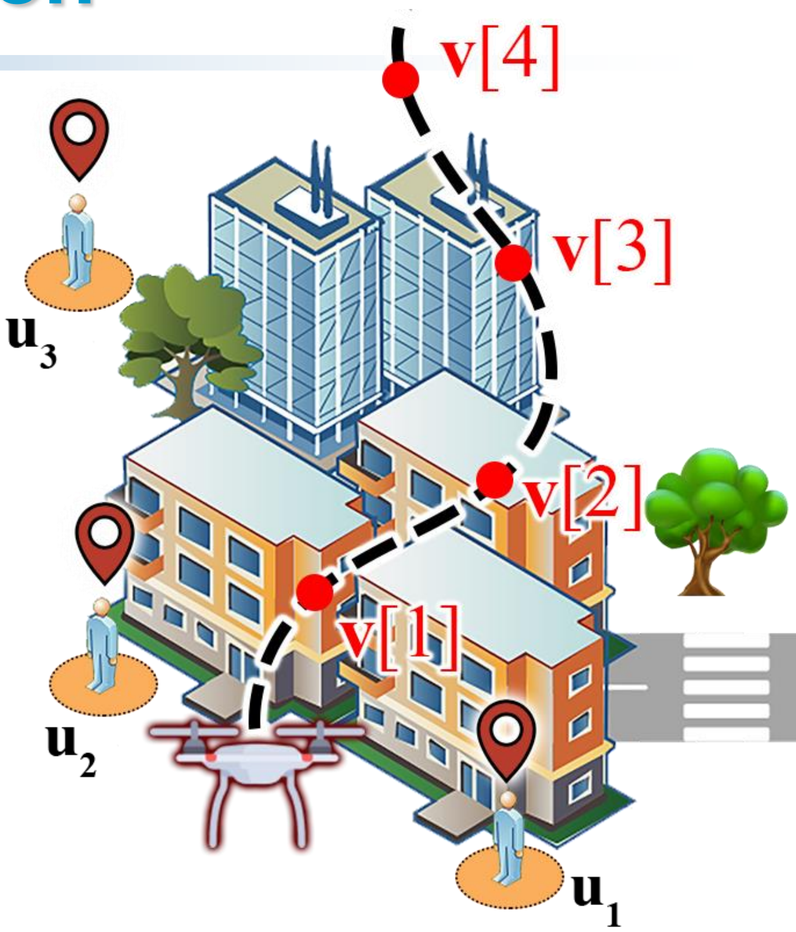
$\mathbf{u}_k$: k-th ground user location

$\boldsymbol{\theta}$: channel parameters (e.g. $\boldsymbol{\theta} = [\theta_1, \theta_2, \cdots]^T$)

$f(.)$: channel model

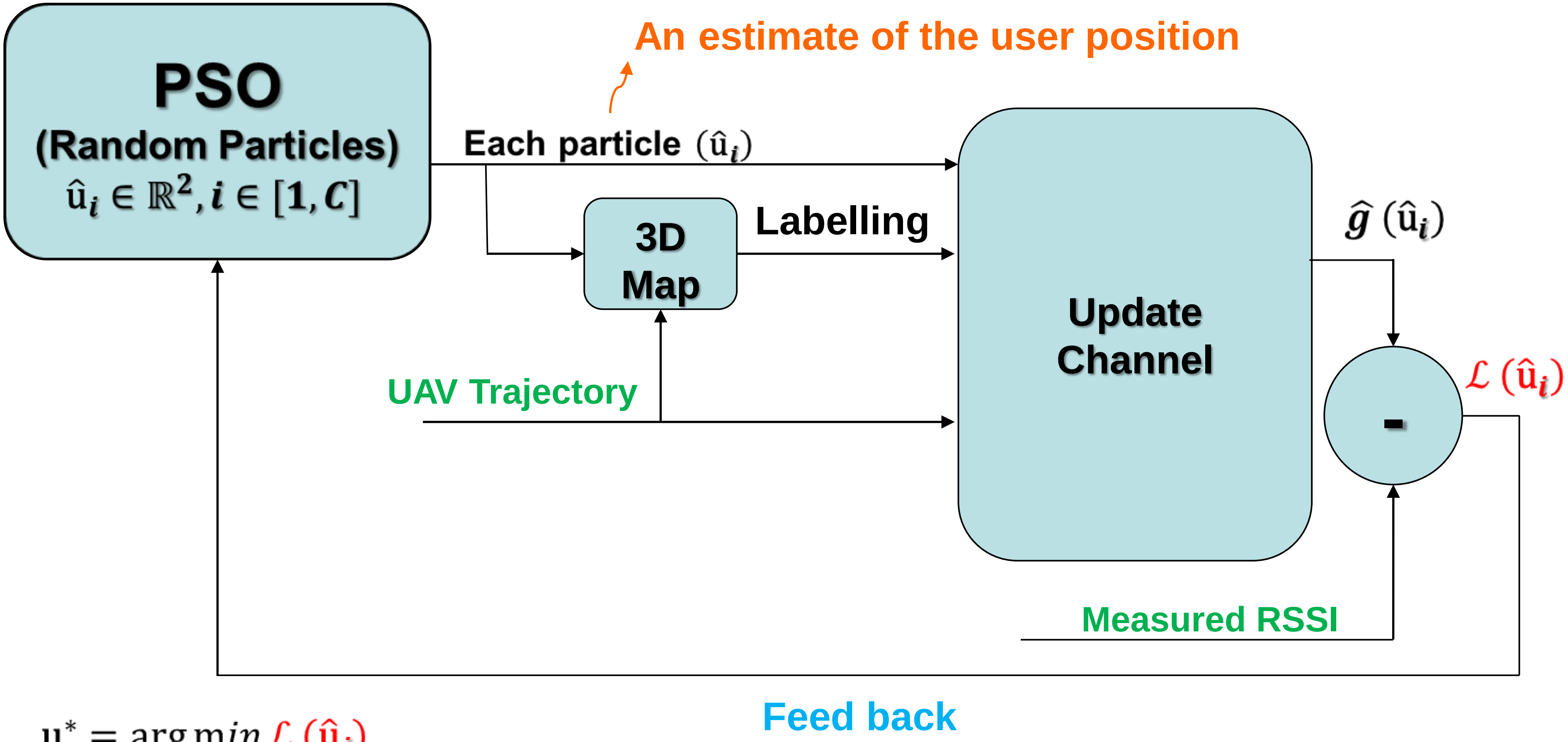
$\mathbf{v}_n$: n-th UAV location

$\gamma_{n,k}$: RSS of the n-th UAV location and the k-th node



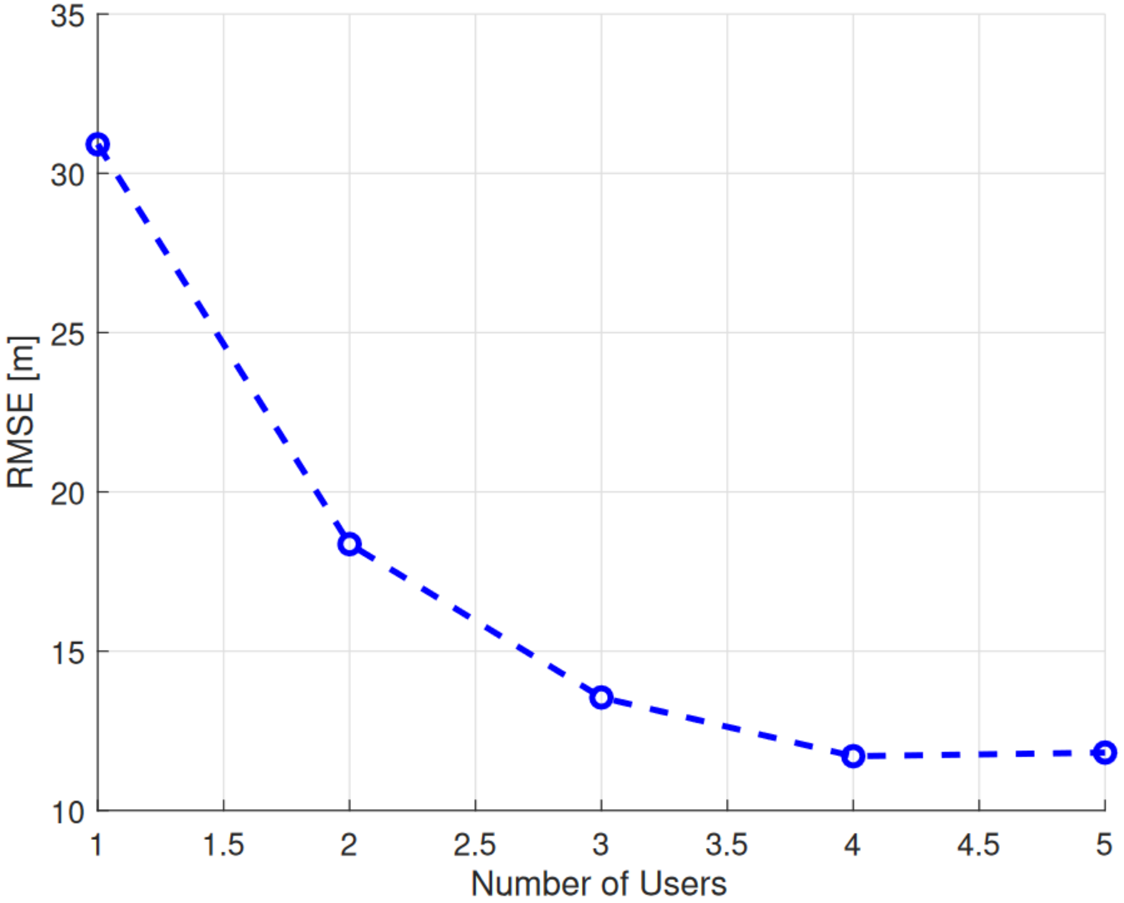
Particle-based UE Localization

*** Measurements: {UAV locations, RSSI}**



$$\mathbf{u}^* = \arg\min_{\hat{\mathbf{u}}_i} \mathcal{L}\,(\hat{\mathbf{u}}_i)$$

Localizing more than one user is easier..



Performance improves with more users! (if user-specific measurements)

But still not enough accuracy ☹

AI-augmented path loss model

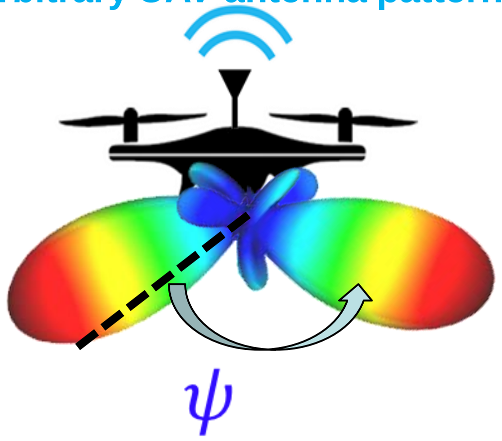
- **Impactful parameters:**

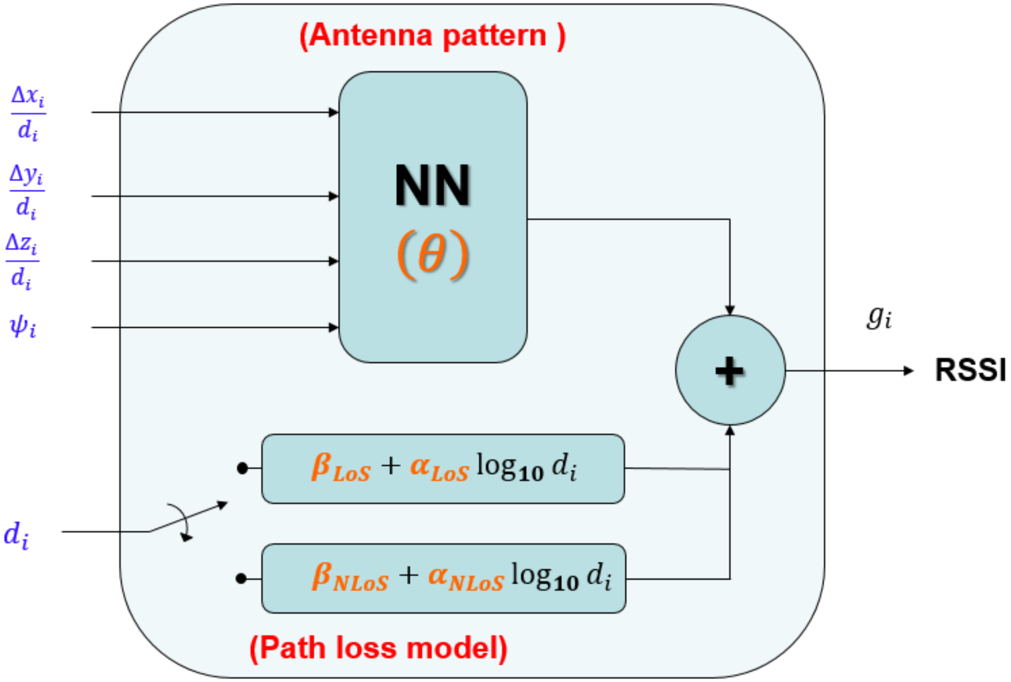
Distance $d = \|\mathbf{v} - \mathbf{u}\|$

Relative position $\Delta X = [\Delta x, \Delta y, \Delta z]$

UAV's heading angle ψ (YAW)

(arbitrary UAV antenna pattern)





(Antenna pattern)

$\frac{\Delta x_i}{d_i}$

$\frac{\Delta y_i}{d_i}$

$\frac{\Delta z_i}{d_i}$

ψ_i

NN

(θ)

g_i

+

RSSI

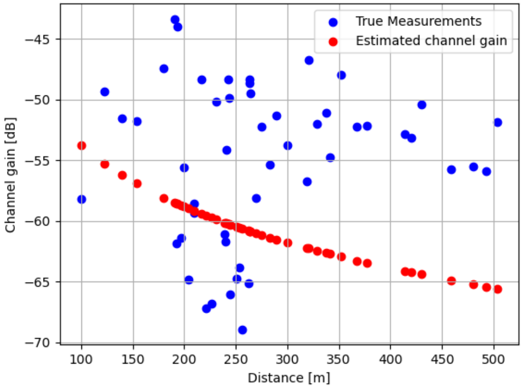
d_i

$\beta_{LoS} + \alpha_{LoS} \log_{10} d_i$

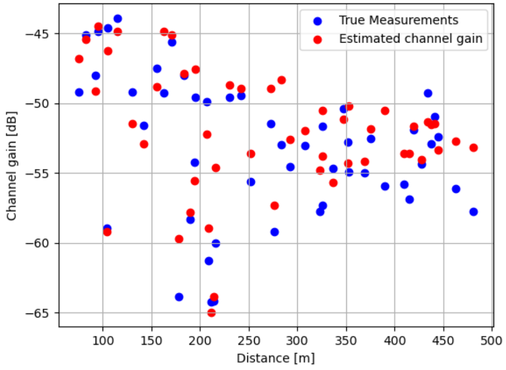
$\beta_{NLoS} + \alpha_{NLoS} \log_{10} d_i$

(Path loss model)

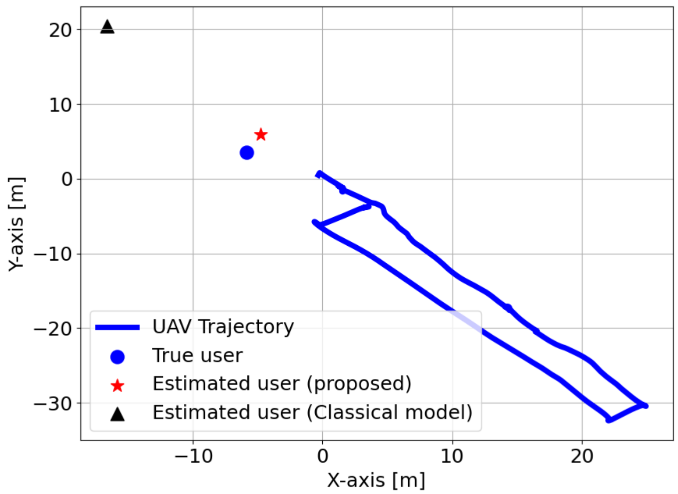
Classical path loss model

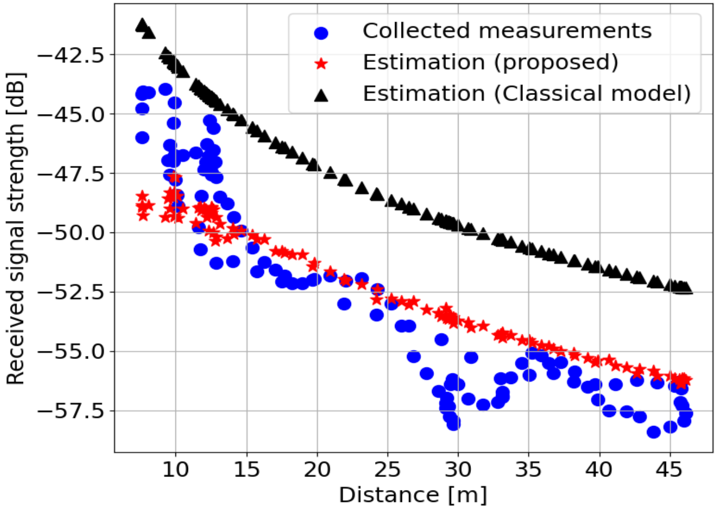


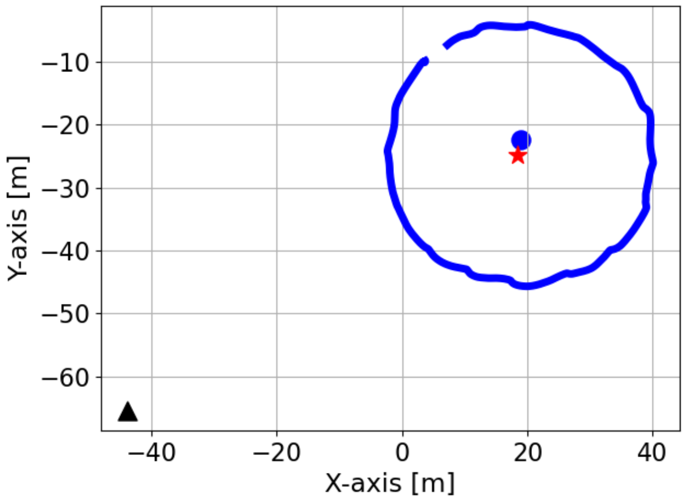
Hybrid DNN-based model

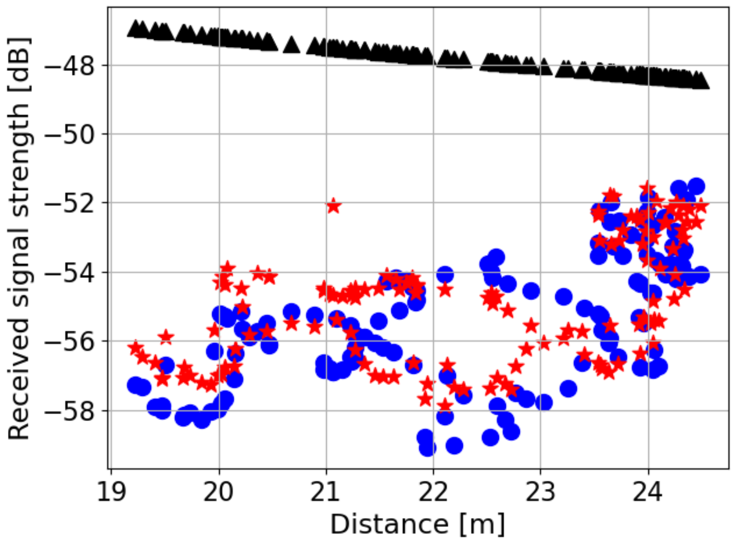


Experimental Results

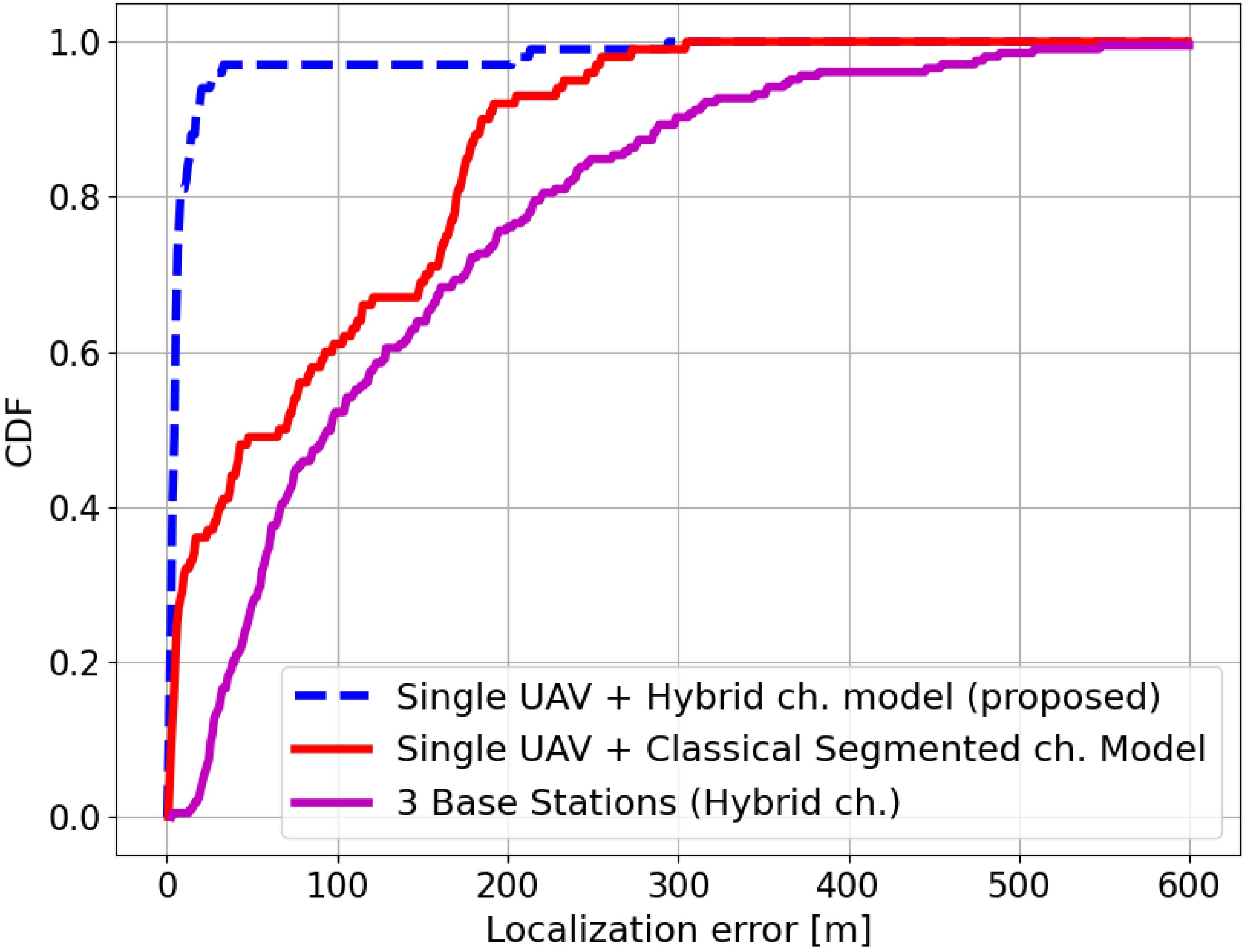




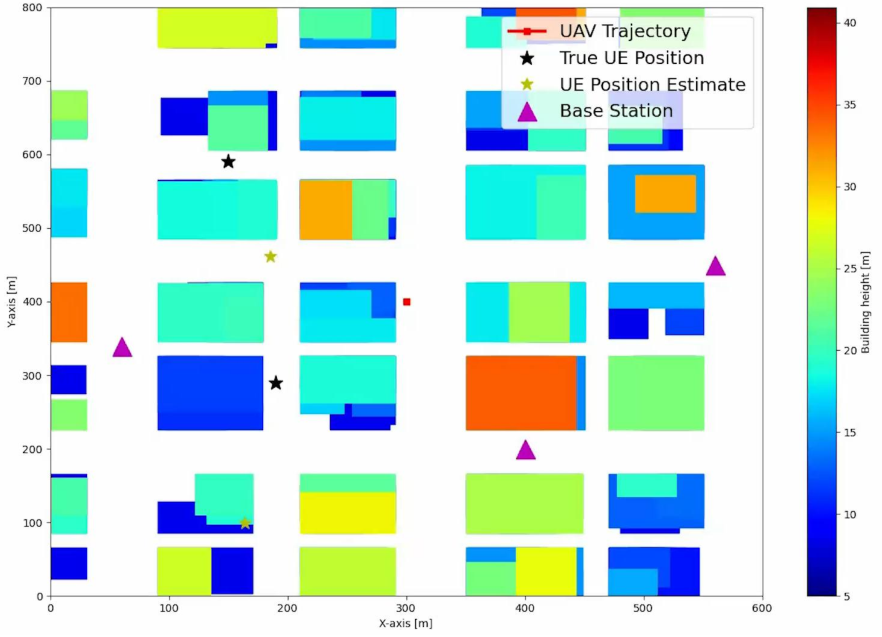


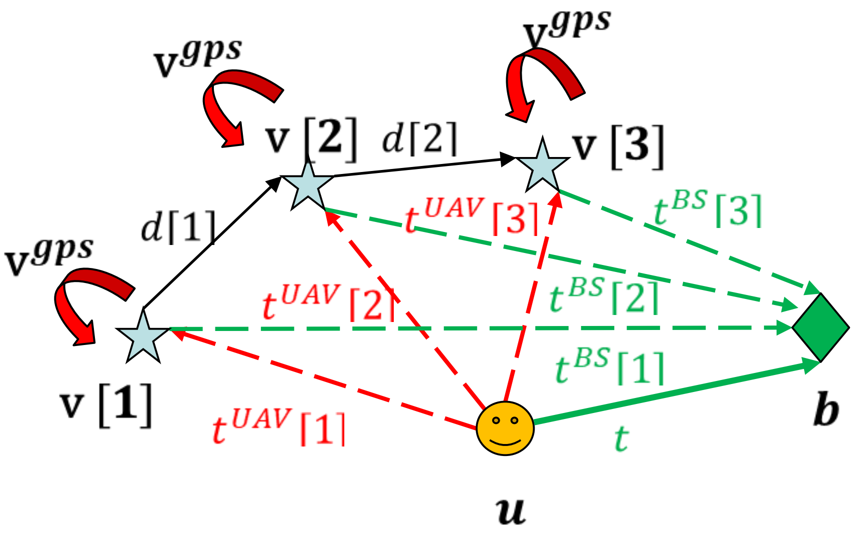


UAV-based vs. fixed BS-based localization



80MHz BW ToA-based localization (Graph-based SLAM)





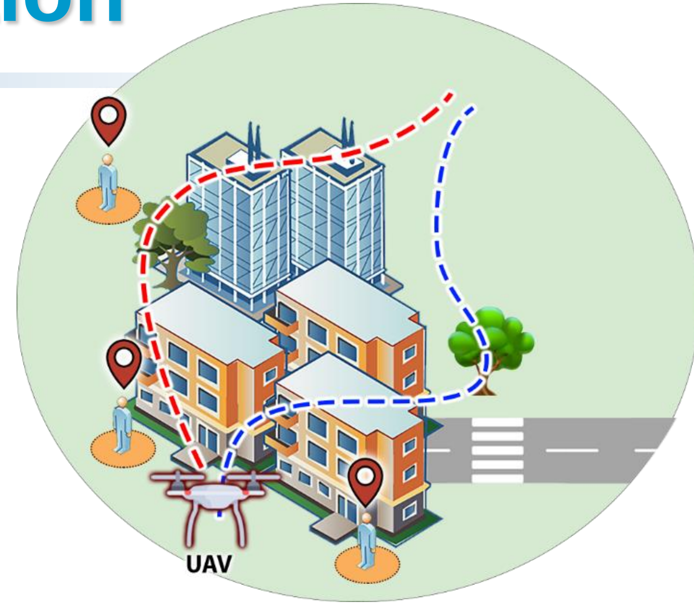
- **UAV Altitude: 80m (average building height 40m)**
- **UAV mission: 20sec**
- **BSs Altitude: 25m**

Model parameters:

- **ToA "noise" LoS $\approx$ 2 m**
- **ToA "noise" NLoS $\approx$ 50 m**
- **UAV GPS noise$\approx$ 5 m**

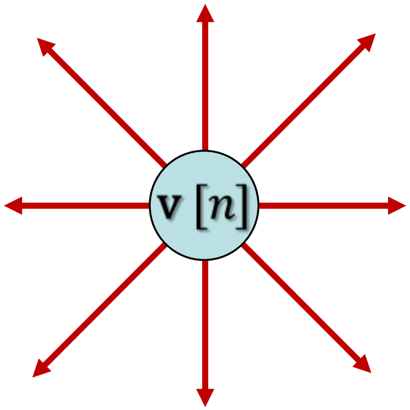
O. Esrafilian, R. Gangula, and D. Gesbert, "Map-based active user localization in UAV-aided wireless networks", 2022.

Active Learning for localization



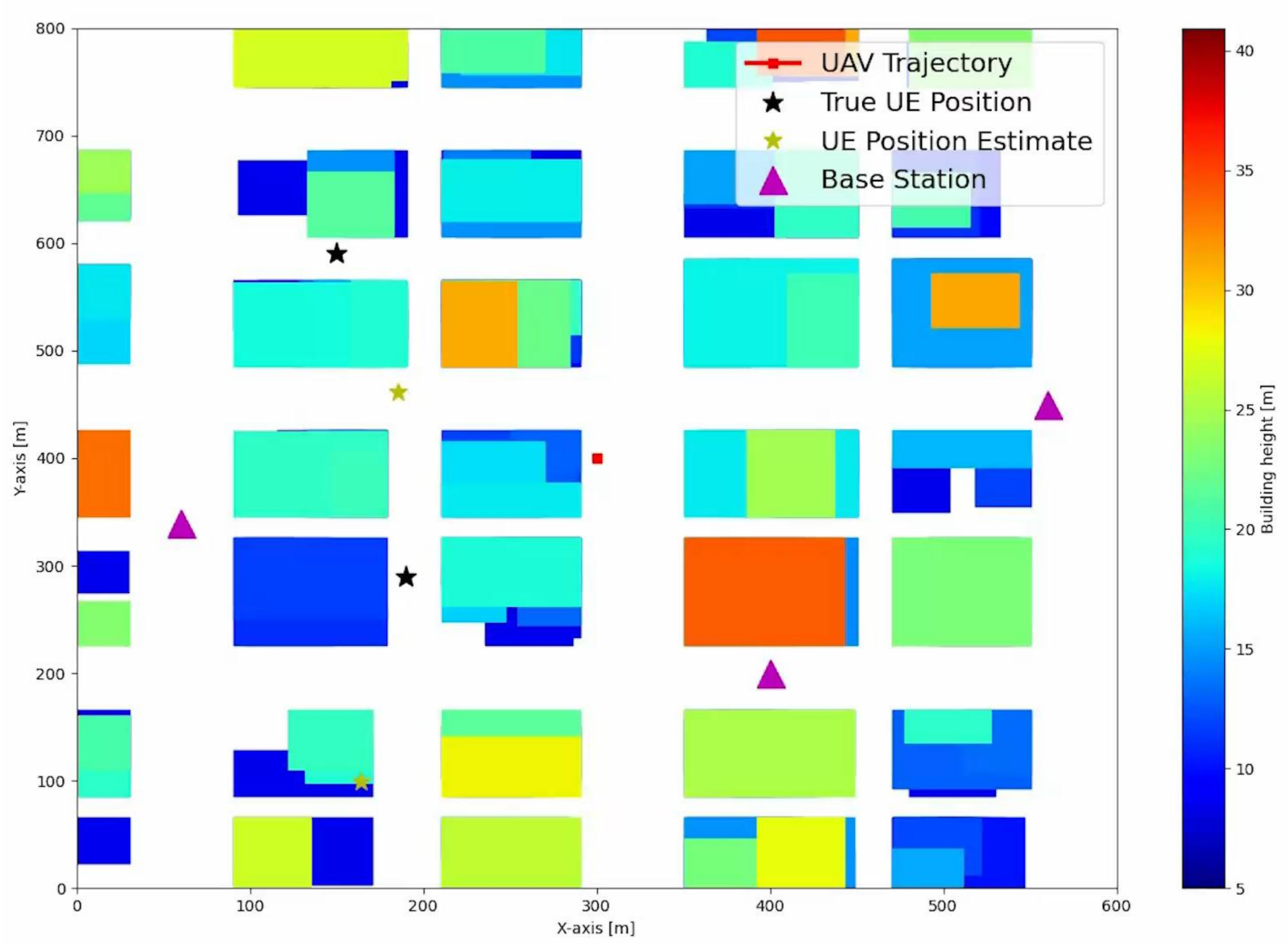
- Active learning to accelerate localization and channel estimation process
- Optimize UAV moves based on Fisher Information matrix (greedy updates).
- Intuition: Trigger most informative measurements

$$\begin{aligned} \min_{\chi=\{\mathrm{v}[1],\cdots,\mathrm{v}[N]\}} \quad & tr(\boldsymbol{F}^{-1}_{N,\mathrm{LoS}} + \boldsymbol{F}^{-1}_{N,\mathrm{NLoS}}) \\ \text{s.t.} \quad & T_F \leq T \\ & \mathrm{v}[1] = \mathrm{v_I}, \mathrm{v}[N] = \mathrm{v_F} \end{aligned}$$



[O. Esrafilian, R. Gangula, D. Gesbert, "3D Map-based Trajectory Design in UAV-aided Wireless Localization Systems", IEEE Internet of Things Journal, April 2020]

Simulation


UAV Trajectory
True UE Position
UE Position Estimate
Base Station
800
700
600
500
400
300
200
100
0
Y-axis [m]
0
100
200
300
400
500
600
X-axis [m]
40
35
30
25
20
15
10
5
Building height [m]

-

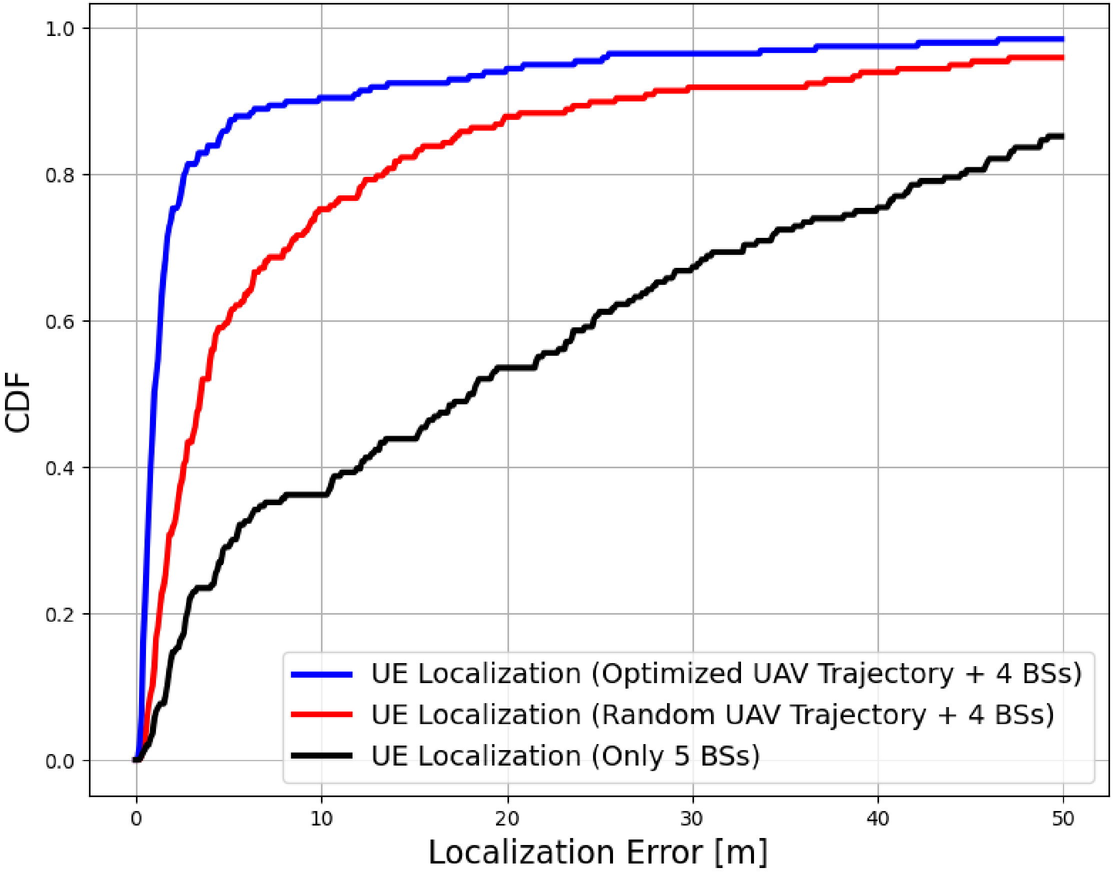
ToA-based localization: BS vs UAV

Measurement model:

- ToA "noise" LoS $\approx$ 2 m
- ToA "noise" NLoS $\approx$ 50 m
- UAV GPS "noise" $\approx$ 5 m

System Model:

- UAV Altitude: 80m
- UAV Trajectory Length: 800m
- BSs Altitude: 25m

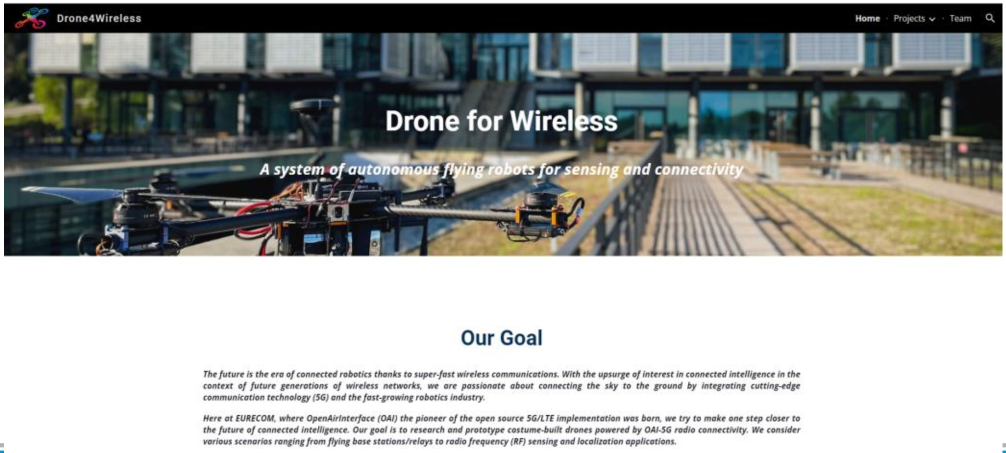


O. Esrafilian, R. Gangula, and D. Gesbert. "UAV Trajectory Optimization and Tracking for User Localization in Wireless Networks." *arXiv preprint arXiv:2305.14959,* 2023.

Learned lessons

- Robot-aided network sensing gives rich 3D sensing capability
- 3D Mapping key to reliability
- Active learning help “produce” best measurement data
- Digital twin models can help boost learning time

More about our works on: https://www.drone4wireless.com



Drone for Wireless

A system of autonomous flying robots for sensing and connectivity

Our Goal

The future is the era of connected robotics thanks to super-fast wireless communications. With the upsurge of interest in connected intelligence in the context of future generations of wireless networks, we are passionate about connecting the sky to the ground by integrating cutting-edge communication technology (5G) and the fast-growing robotics industry.

Here at EURECOM, where OpenAirInterface (OAI) the pioneer of the open source 5G/LTE implementation was born, we try to make one step closer to the future of connected intelligence. Our goal is to research and prototype costume-built drones powered by OAI-5G radio connectivity. We consider various scenarios ranging from flying base stations/relays to radio frequency (RF) sensing and localization applications.