Robot-Augmented Sensing and Localization for 6G Networks

One6G Seminar

May 5th, 2022

Prof. David Gesbert

EURECOM, Sophia-Antipolis, France

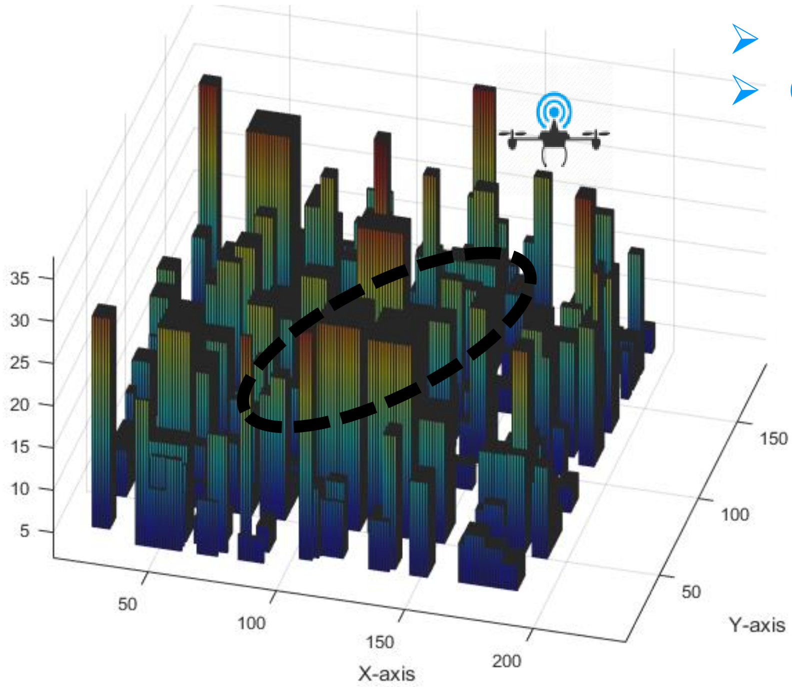
With team members Omid Esrafilian, Rajeev Gangula

Outline

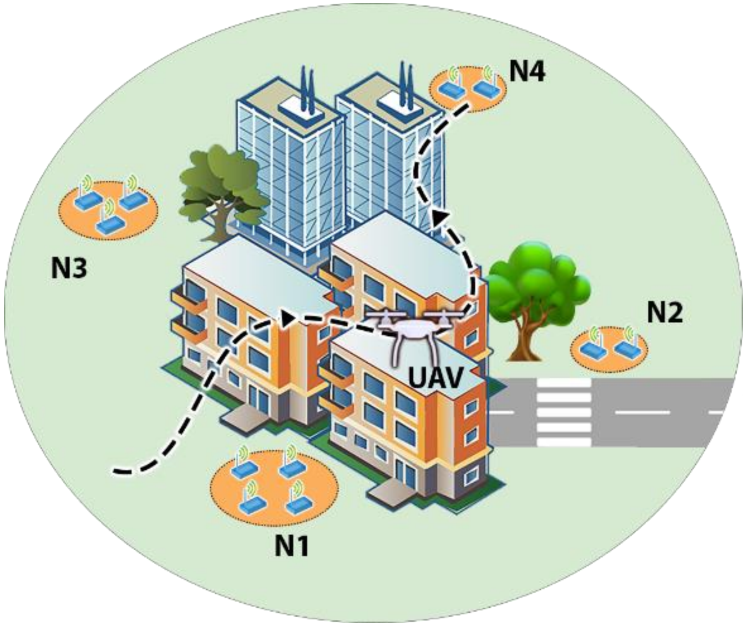
- Scenarios for robot-augmented sensing
- Dealing with NLoS: Map-based channel models
- RSSI-based UE localization: Can we do it?
- Active learning for UE localization
- Perspectives

Robot-augmented RF Sensing

- Injecting a robot in the network for sensing: Why?
  - Robot-borne (UAV, cars,..) enrich sensing data space
  - Opportunity to move freely to create meaningful data

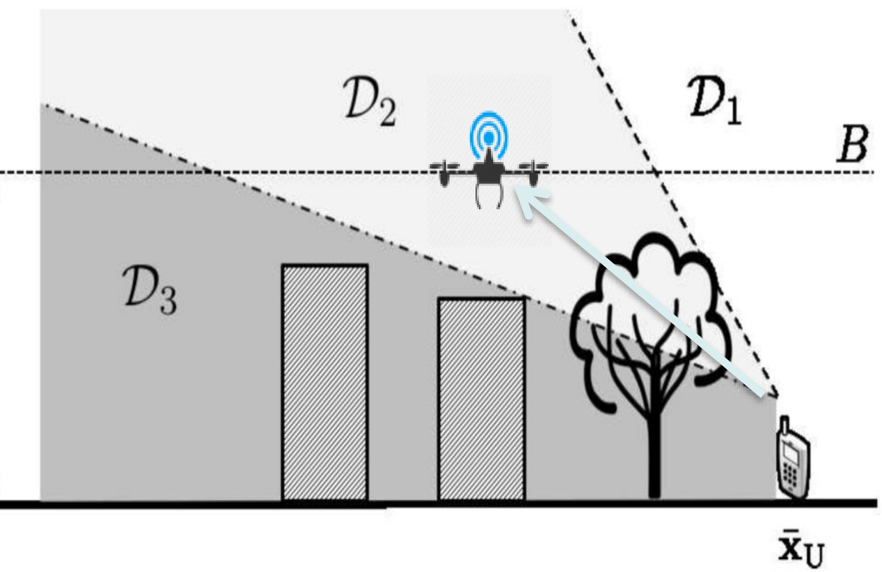


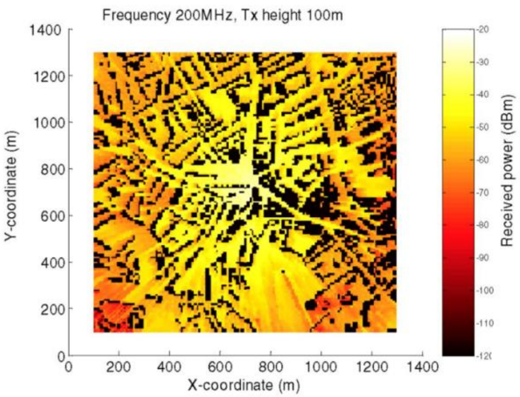
Robot-aided mapping
Radio map, 3D Map reconstruction,
Outdoor, indoor (factory setting)



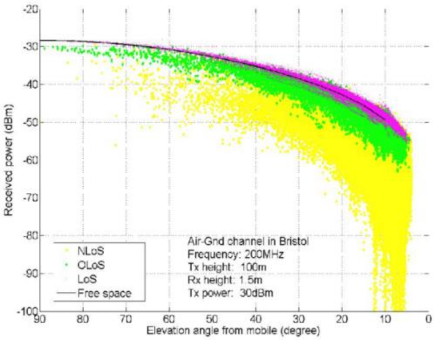
Robot-aided localization
Node localization, SLAM

Segmented Channel Path Loss Models





Received power map UAV 100 meter above center of Bristol



Av. RX power

Fixed offset

shadowing

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

distance

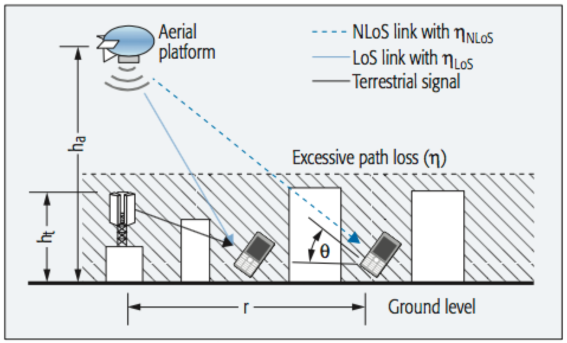
Path loss exponent

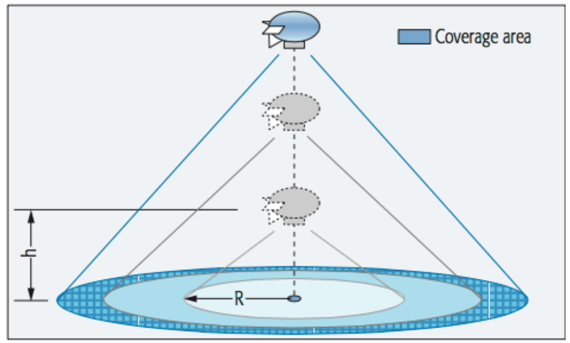
Class s=1,2,3,..
e.g. s=1 for LoS
s=2 for NLoS, etc.

Probabilistic vs map-based models

▪ Probabilistic LoS prediction

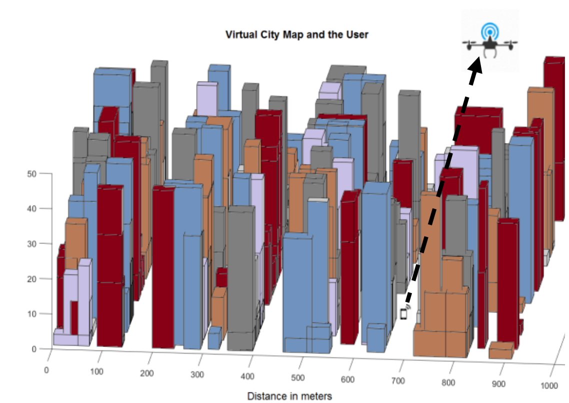
➢ Ex: LoS probability model $$\mathrm{P}(\mathrm{LoS}, \theta) = \frac{1}{1 + a \exp\left(-b[\theta - a]\right)}$$

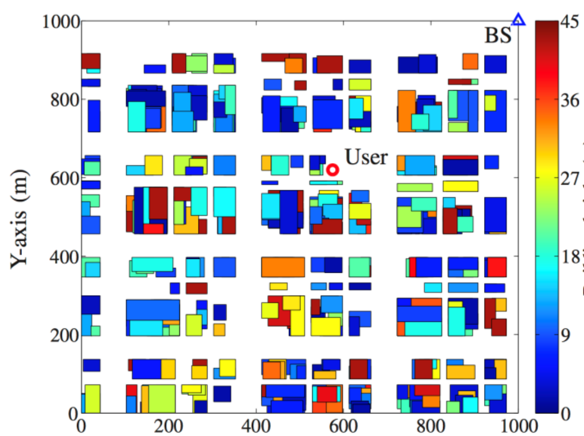


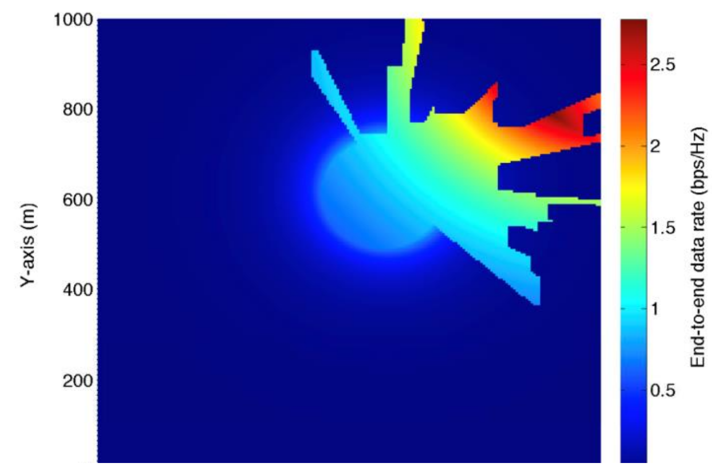


[Hourani14] A. Al-Hourani, S. Kandeepan, and S. Lardner, “Optimal LAP Altitude for Maximum Coverage”, *IEEE Comm. Lett.*, 2014.

▪ map-based LoS prediction







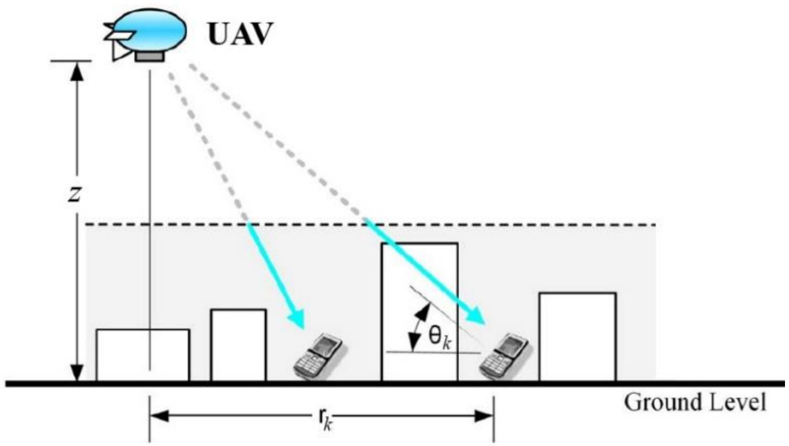
D. Gesbert, O. Esrafilian, J. Chen, R. Gangula, U. Mitra, "UAV-aided RF Mapping for Sensing and Connectivity in Wireless Networks", IEEE Communications Magazine, 2022.

Local probabilistic model (*Map compression*)

Global LOS Probability model:

$$p_k\,[n] = \frac{1}{1+\exp(-a\,\theta_k\,[n]+b)}$$

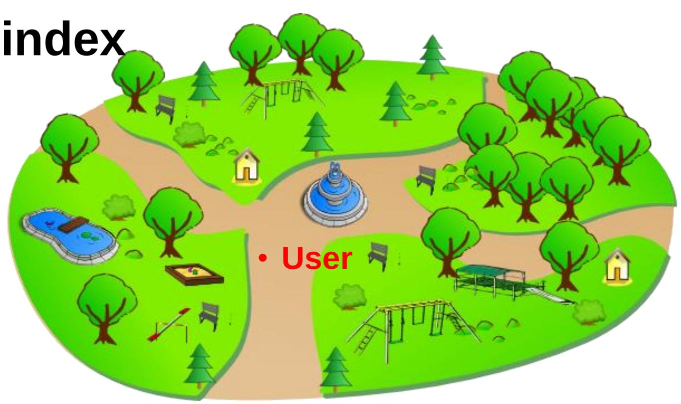
$$\theta_k = \tan^{-1}\left(\frac{z}{r_k}\right)$$



New local map-aided LOS Probability:

$$p_k[n] = \frac{1}{1+\exp(-a_k\theta_k[n]+b_k)}$$

User index



RSSI-based UE Localization

- **Problem formulation:**

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

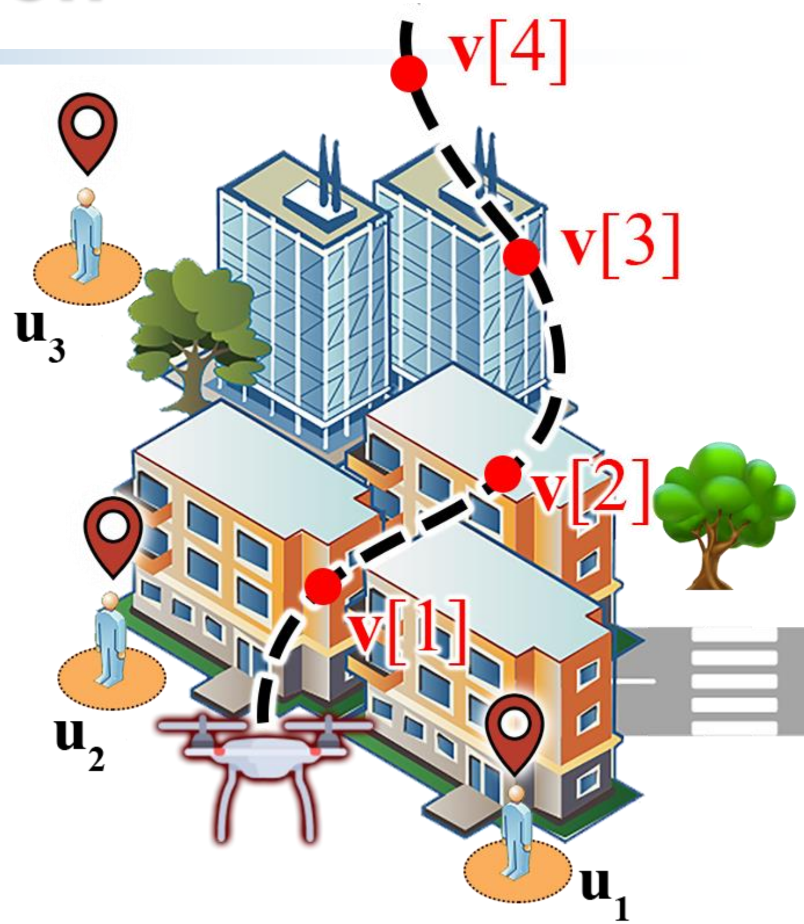
$\mathbf{u}_k$: k-th ground user location

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

$f(.)$: channel model

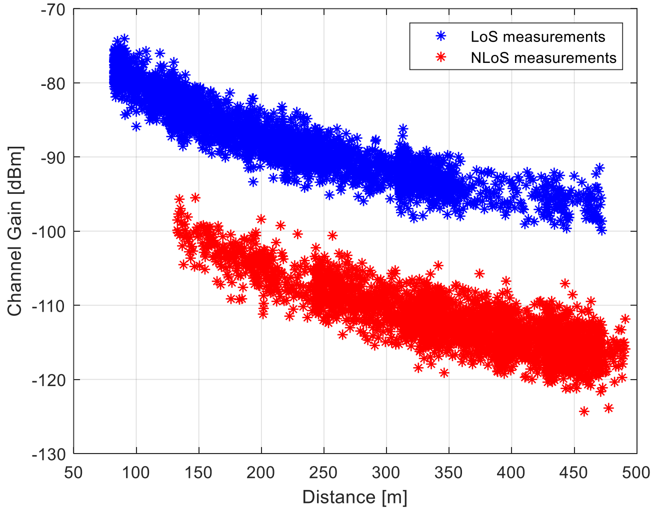
$\mathbf{v}_n$: n-th UAV location

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

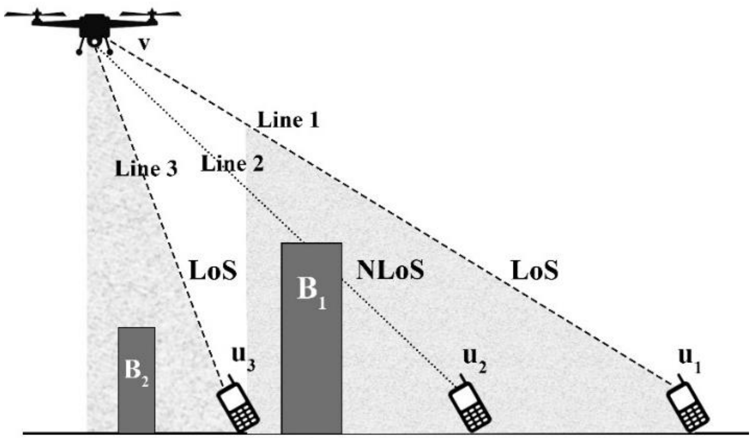


Channel model segment classification

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

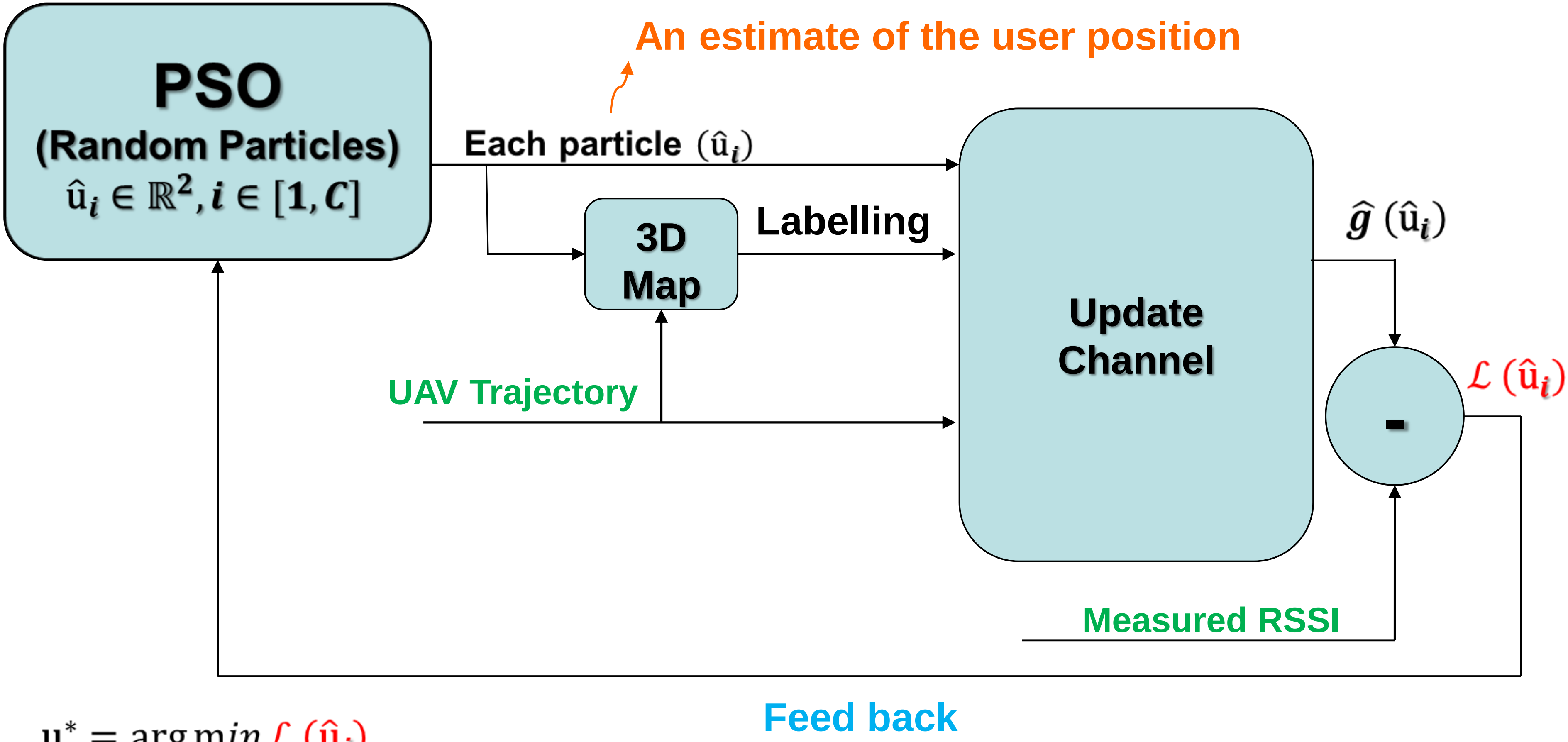


LoS/NLoS



Particle-based UE Localization

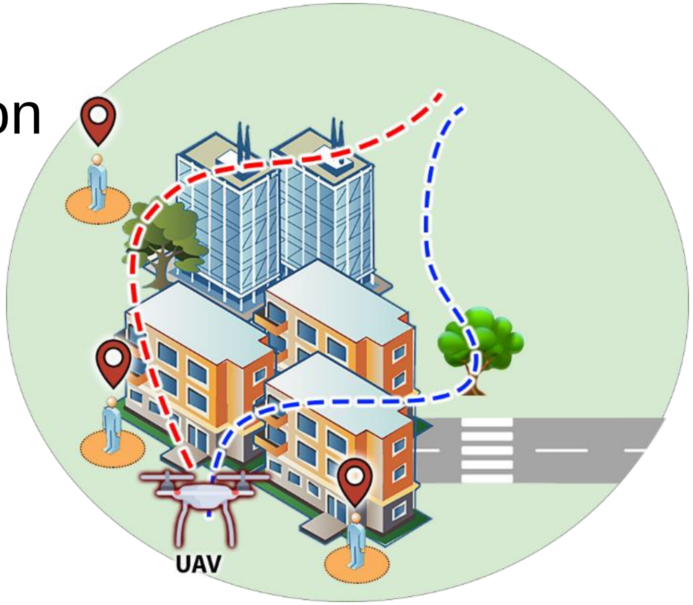
*** Measurements: {UAV locations, RSSI}**



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

Dealing with NLoS: Active Learning for node localization

- Optimize UAV trajectory to accelerate the localization/learning process of UE location and channel model parameters.
- Active learning based on Fisher Information matrix (greedy updates).
- Intuition: Trigger most informative measurements



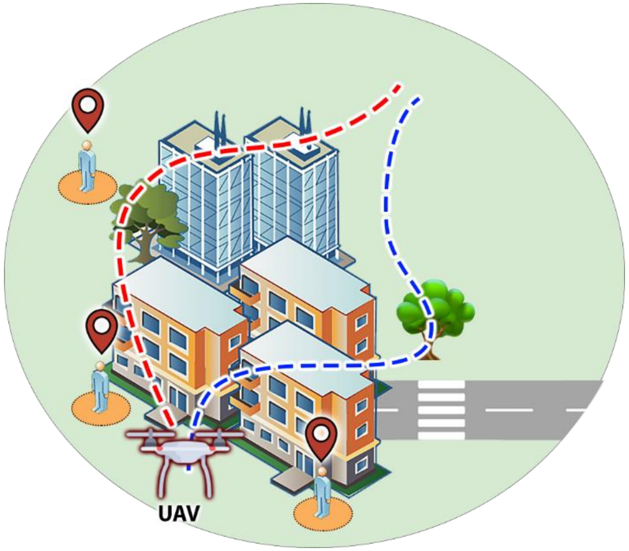
[O. Esrafilian, R. Gangula, D. Gesbert, "3D Map-based Trajectory Design in UAV-aided Wireless Localization Systems", IEEE Internet of Things Journal, April 2020]

Active Learning for node localization

- Design a trajectory (over discrete time) such that

$$\begin{aligned}\min_{\chi=\{\mathrm{v}[1],\cdots,\mathrm{v}[N]\}} \quad & MSE(\phi_{\mathrm{LoS}}) + MSE(\phi_{\mathrm{NLoS}}) \\ \text{s.t.} \quad & T_F \leq T \\ & \mathrm{v}[1] = \mathrm{v}_{\mathrm{I}}, \mathrm{v}[N] = \mathrm{v}_{\mathrm{F}}\end{aligned}$$

Where $\phi_s = \{\beta_s, \alpha_s, \mathrm{u}_1, \cdots, \mathrm{u}_K\}$.



- Using Cramér–Rao bound (C.R.B)

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

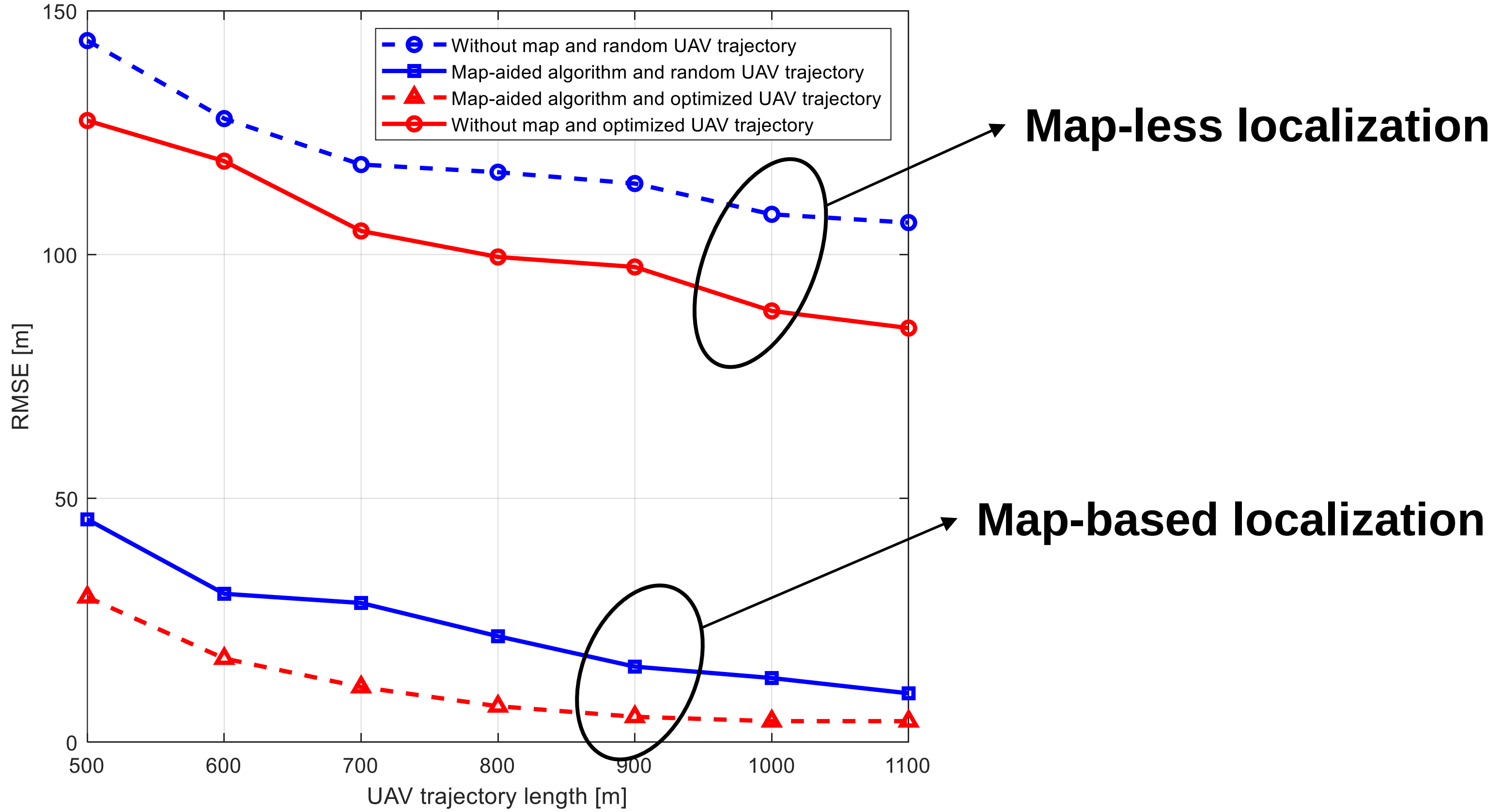
- $\boldsymbol{F}_{N,s}^{-1}$: Inverse of FIM up to time N and segment $s \in \{\mathrm{LoS}, \mathrm{NLoS}\}$

$$\boxed{\boldsymbol{F}_{N,s}^{-1} = \boldsymbol{F}_{N-1,s}^{-1} + \boldsymbol{R}_{N,s}}$$

is recursive

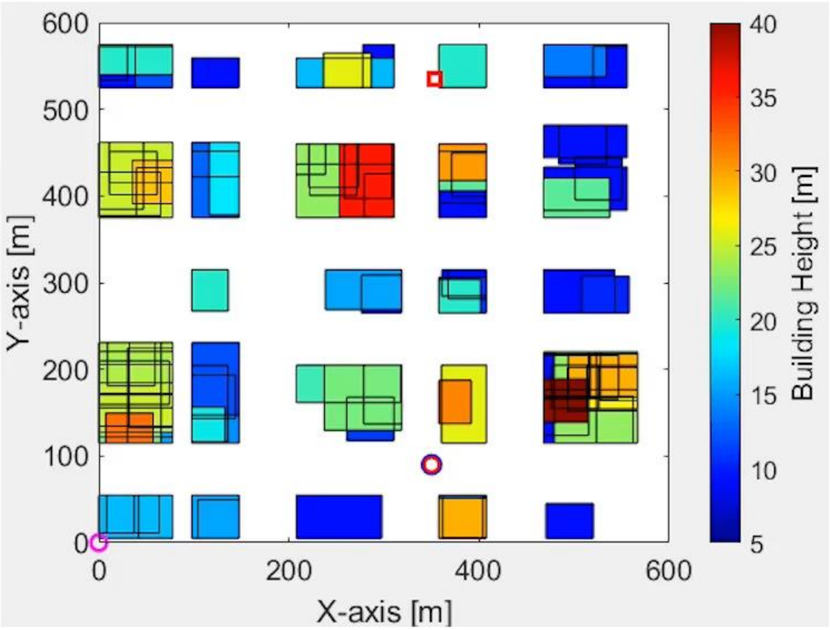
Improvement at time step N

Localization vs. flight time with active learning

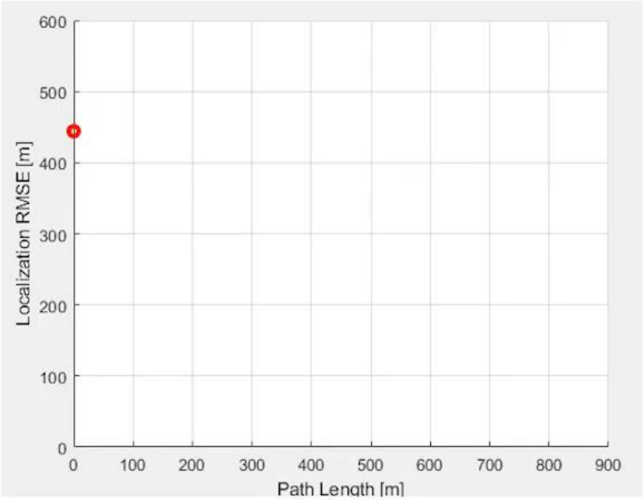


Active Learning for node localization

Fixed altitude: 50 m

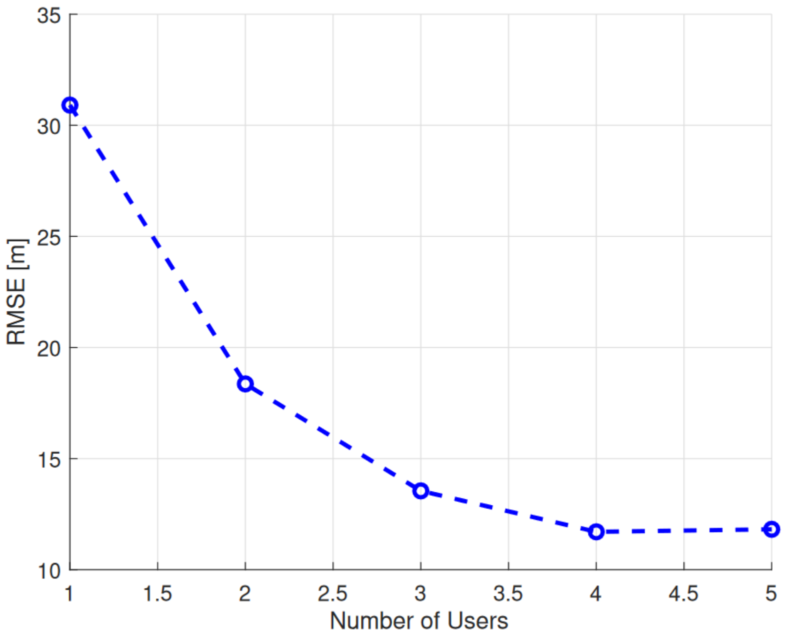


Localization error

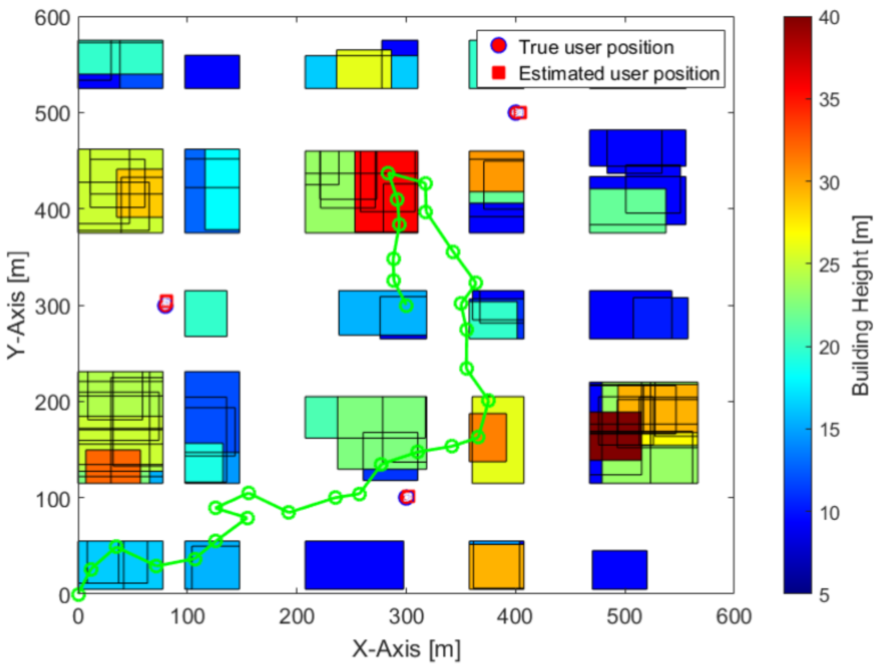


Multi-User Localization performance

Performance improves with more users!



Active learning trajectory for 3-user localization



EURECOM
Sophia Antipolis

Beyond the distance-based path loss model

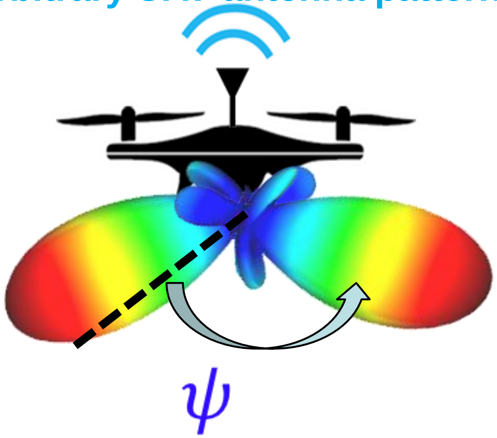
- **Impactful parameters:**

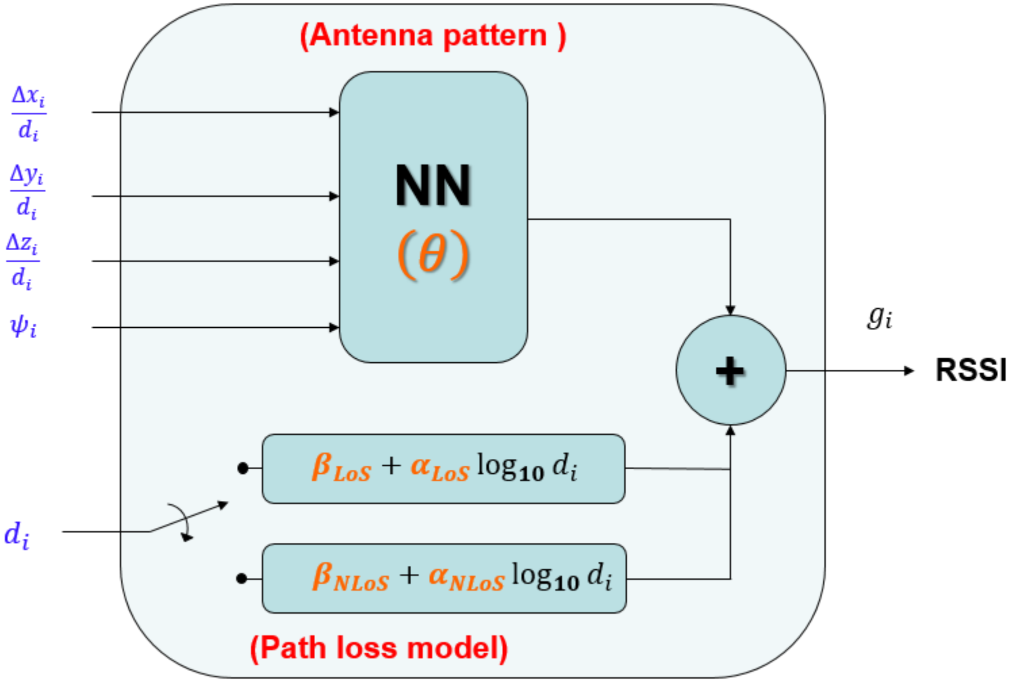
Distance $d = \|\mathbf{v} - \mathbf{u}\|$

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

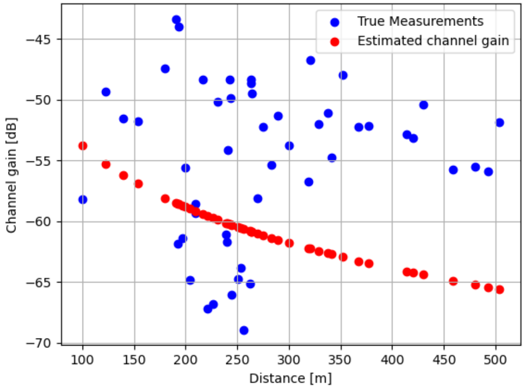
UAV's heading angle ψ (YAW)

(arbitrary UAV antenna pattern)

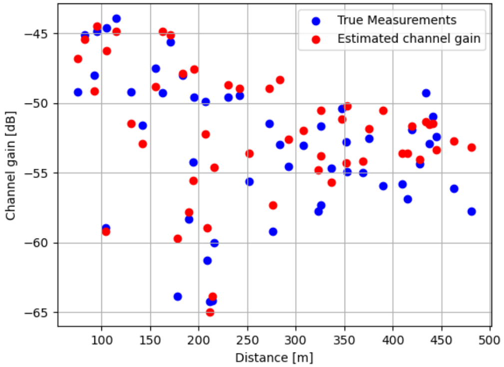




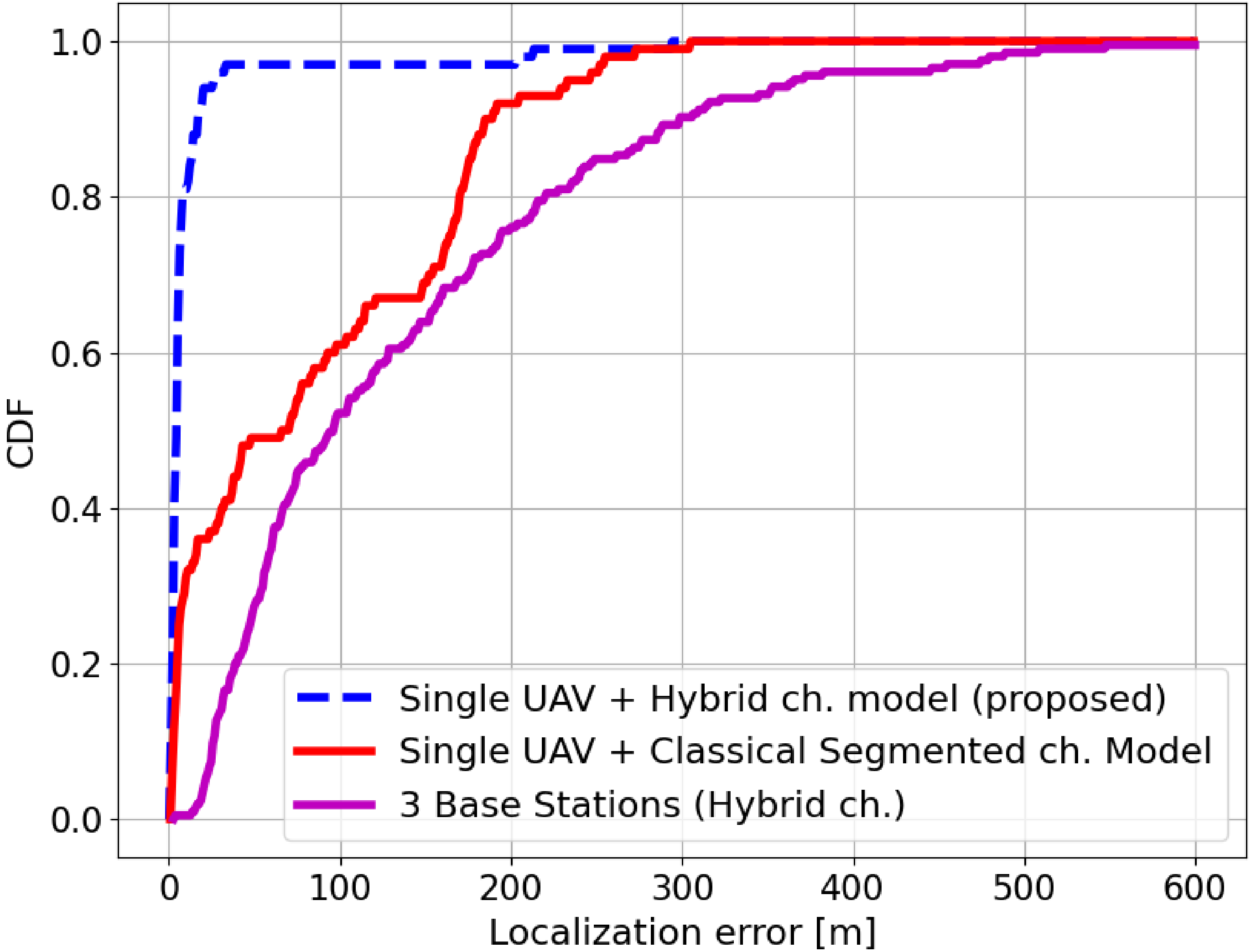
Classical path loss model



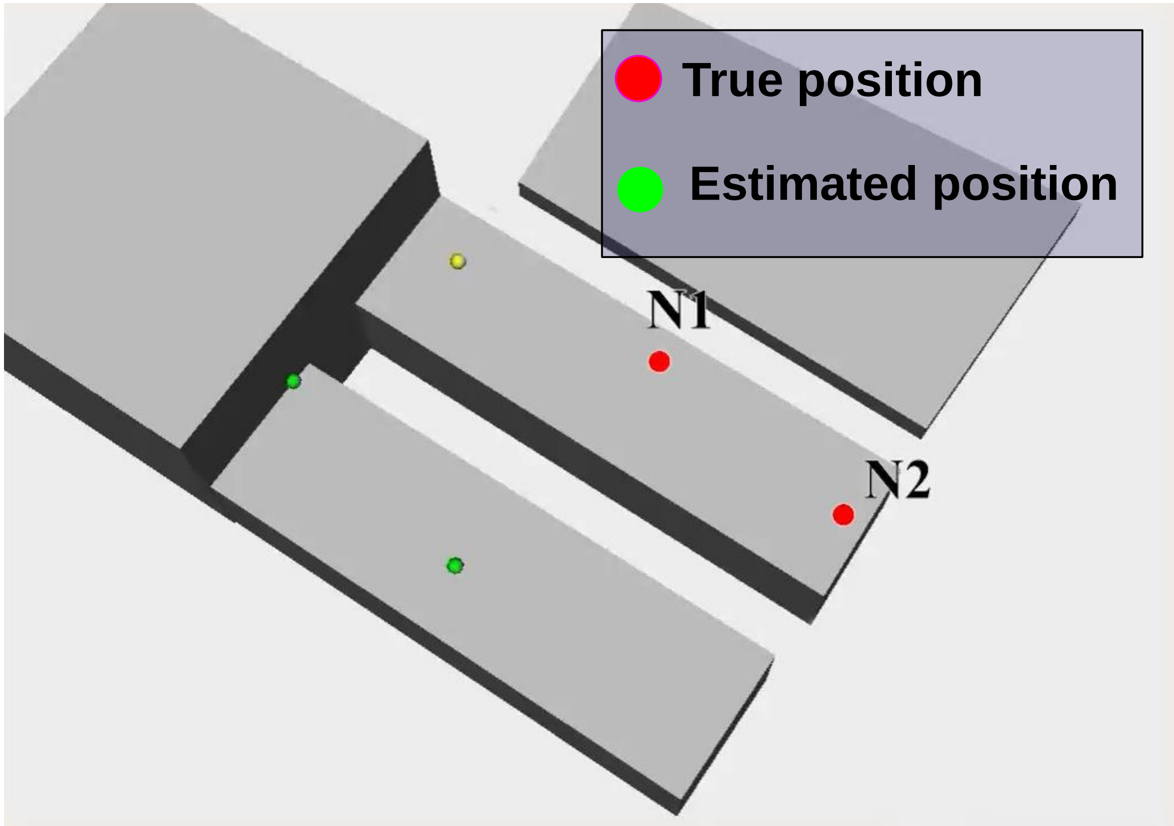
Hybrid DNN-based model



UAV-based vs. fixed BS-based localization

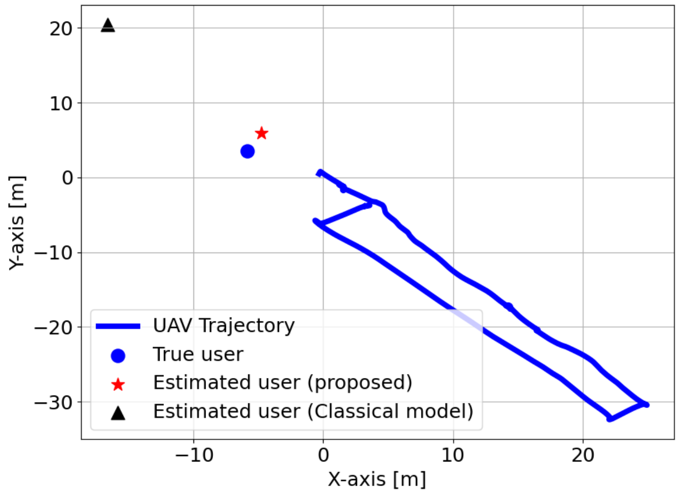


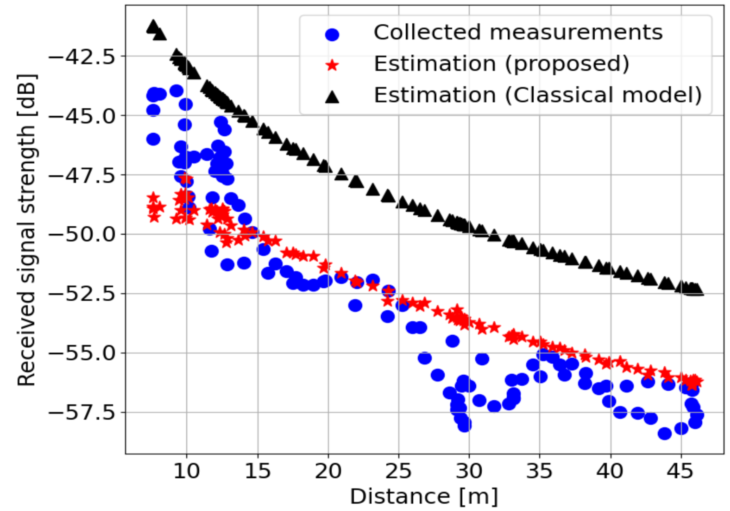
Experiment (multi-user)

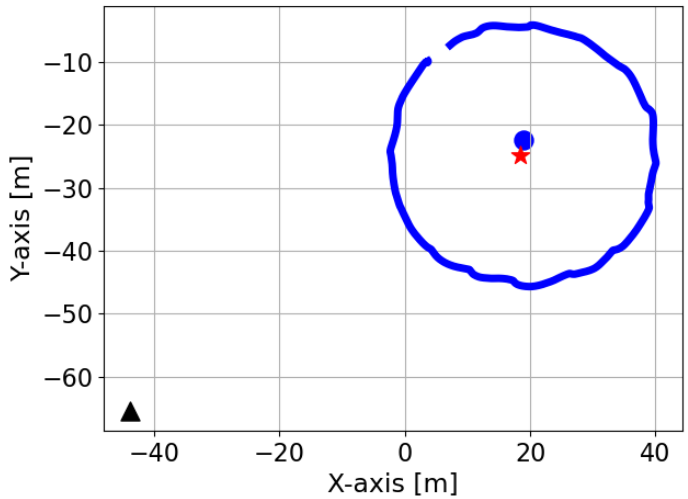


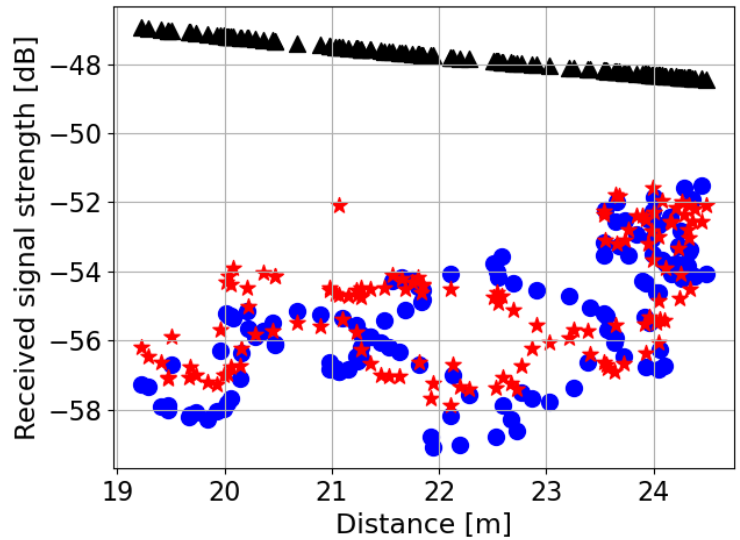
[O. Esrafilian, R. Gangula, D. Gesbert, “UAV-aided Wireless Node Localization Using Hybrid Radio Channel Models”, to appear in IEEE ICC 2022 UAV-5G Workshop.

Experiment Results









Perspectives

- Robot-aided network sensing gives rich 3D sensing capability
- 3D Mapping allows for reliability
- Active learning help “produce” best measurement data
- Ongoing work:
  - Combining RSSI with ToA data (SLAM approach vs. triangulation)
  - Fusion with extended sensing domains (vision, LIDAR, ..)