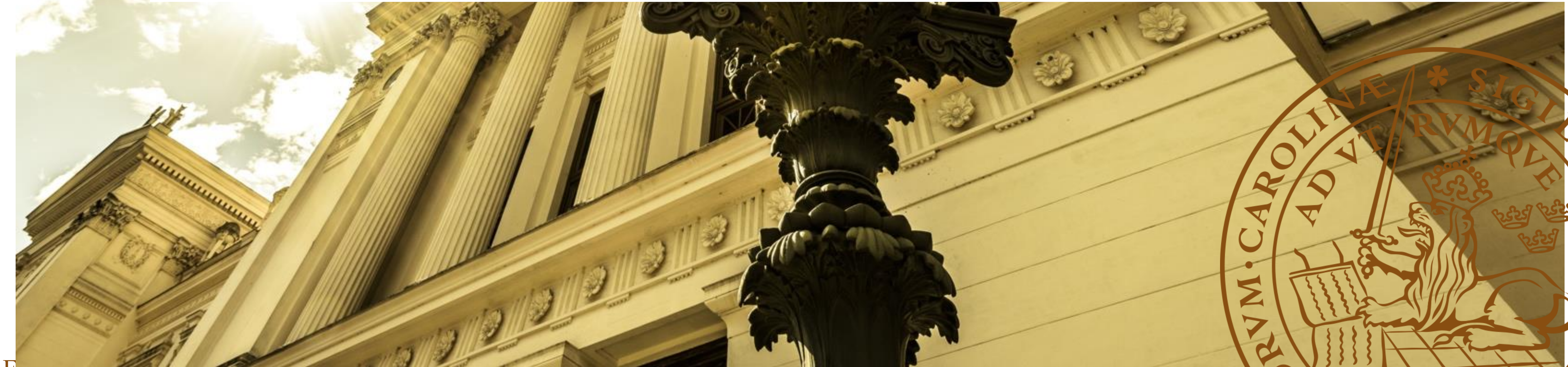
Distributed MIMO Single Snapshot Environment Mapping via Spatial Filtering

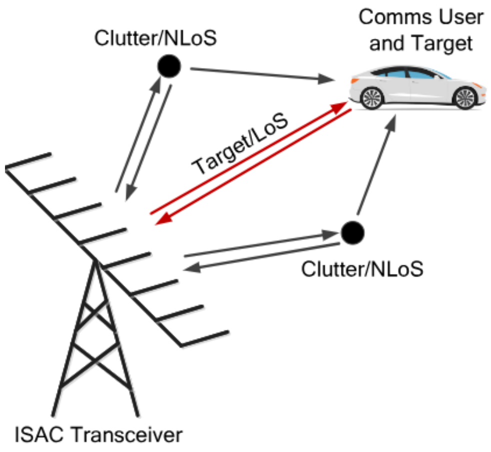
Focus Period Linköping 2026: Wireless Sensing Technologies for Emerging Applications

Yingjie Xu
Department of Electrical and Information Technology, Lund University



Distributed ISAC: a transformative approach for 6G

Integrated Sensing and Communication



Shared frequency band and hardware

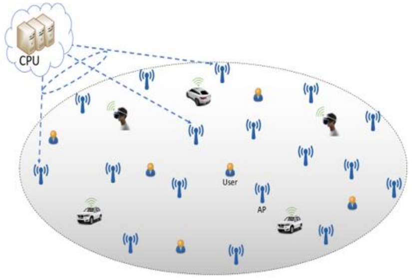
⇩ ⇩

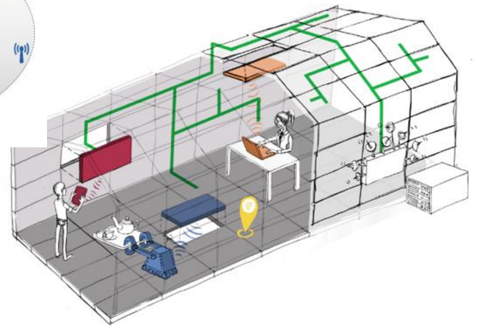
Enhanced spectral efficiency

Reduced hardware costs

&

Distributed/cell-free MIMO





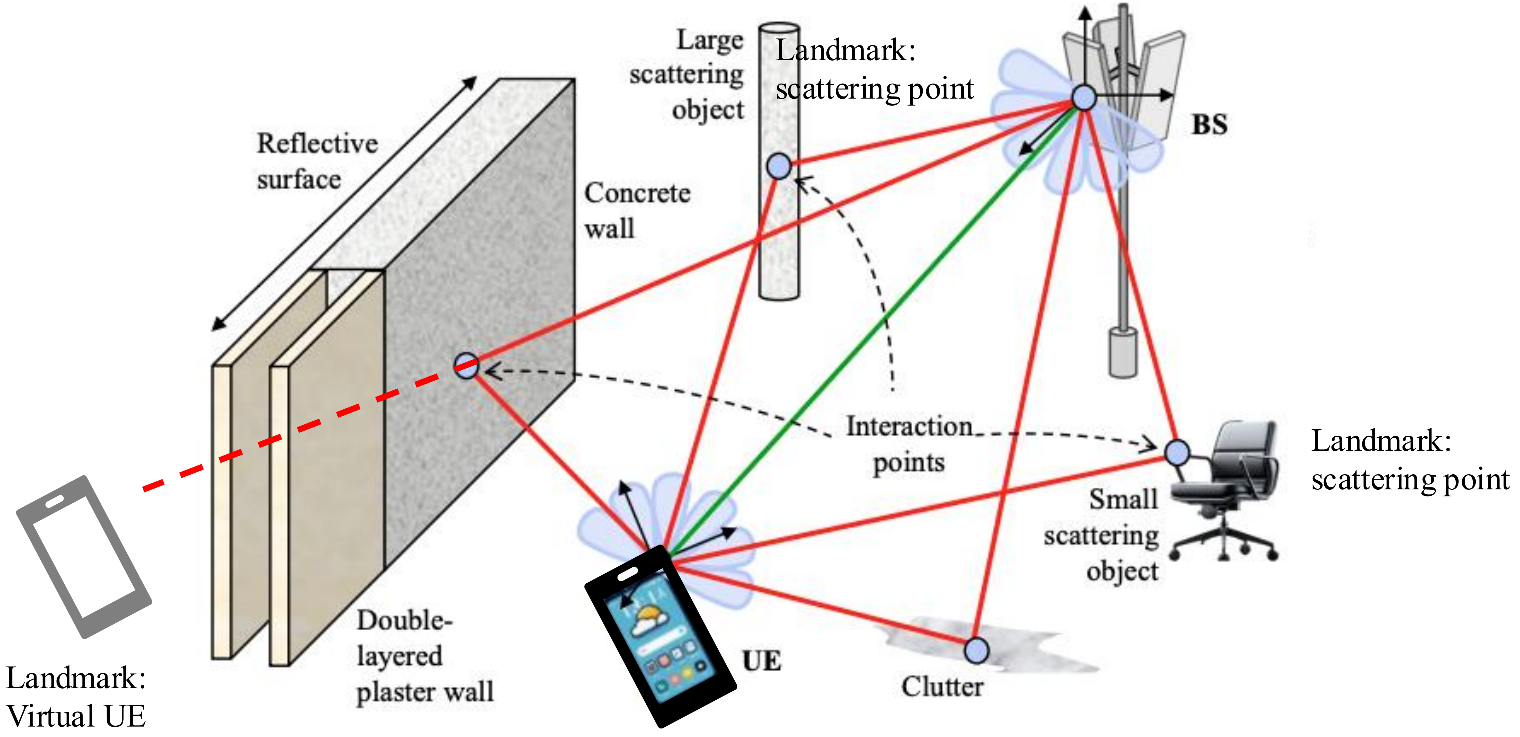
Spatially-distributed nodes

⇩

Spatial diversity, uniform coverage

Radio-based environment mapping

- Radio signals interact with physical environments through multipaths.
- Environment is characterized by different types of landmarks.



Our focus is single-snapshot environment mapping

	Time-Sequential Mapping	Single-Snapshot Mapping
Feature	• Recursive estimation over time • Multiple snapshots of measurements	• Estimate instantaneous landmark states • Ues only a single snapshot of measurements.
Advantage	• Baysiean filtering framework • High accuracy	• Low complexity (maximum-likelihood) • Baseline
Ref.	[1][2][3]	[4][5]

[1] H. Kim et al., "5G mmWave cooperative positioning and mapping using multimodel PHD filter and map Fusion," *IEEE Trans. Wireless Commun.*, vol. 19, no. 6, 2020, pp. 3782–3795.

[2] H. Kim, K. Granstr¨om, L. Svensson, S. Kim, and H. Wymeersch, "PMBM-based SLAM filters in 5G mmWave vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 71, no. 8, pp. 8646–8661, Aug. 2022.

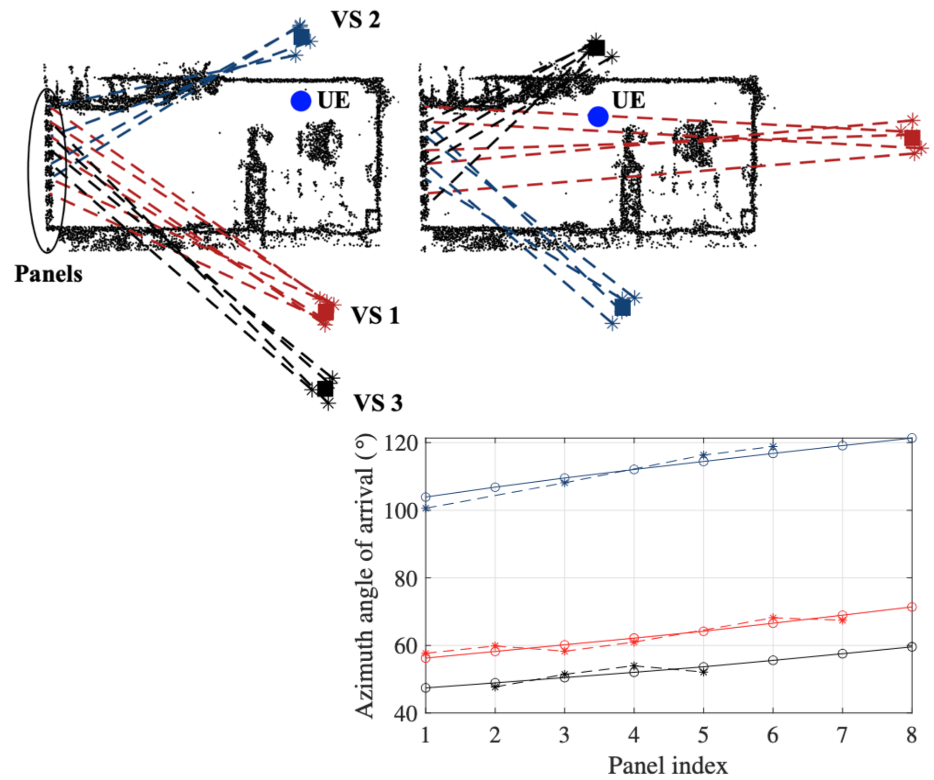
[3] Y. Ge, O. Kaltiokallio, H. Kim, F. Jiang, J. Talvitie, M. Valkama, L. Svensson, S. Kim, and H. Wymeersch, "A computationally efficient EK-PMBM filter for bistatic mmWave radio SLAM," *IEEE J. Sel. Areas Commun.*, vol. 40, no. 7, pp. 2179–2192, Jul. 2022.

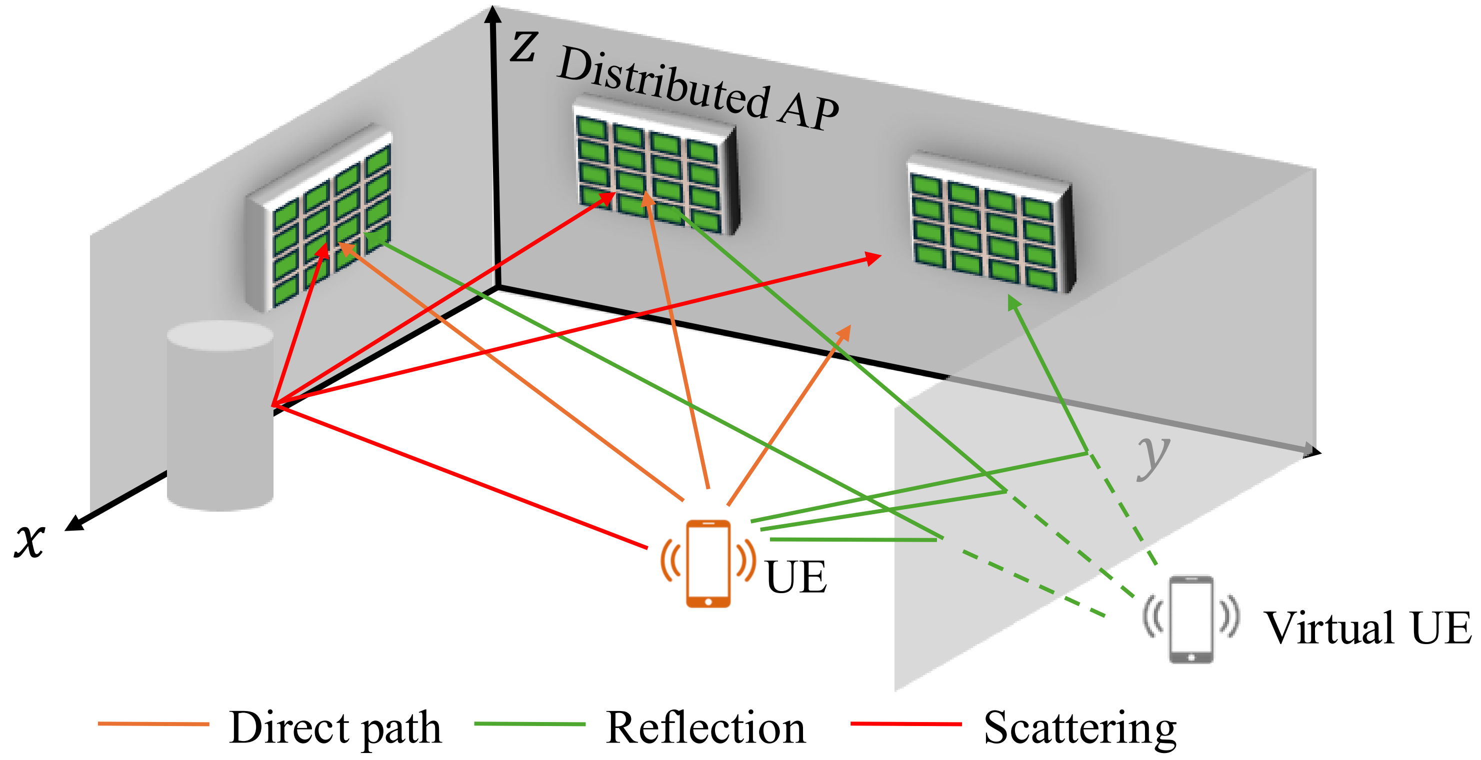
[4] O. Kaltiokallio et al., "Robust snapshot radio SLAM," *IEEE Trans. Veh. Technol.*, early access, Dec. 31, 2024, doi: 10.1109/TVT.2024.3524118.

[5] E. Rastorgueva-Foi et al., "Millimeter-wave radio SLAM: End-to-end processing methods and experimental validation," *IEEE J. Sel. Areas Commun.,* vol. 42, no. 9, pp. 2550–2567, Sep. 2024.

Distributed MIMO provides spatial diversity

Spherical wavefront propagation [1]





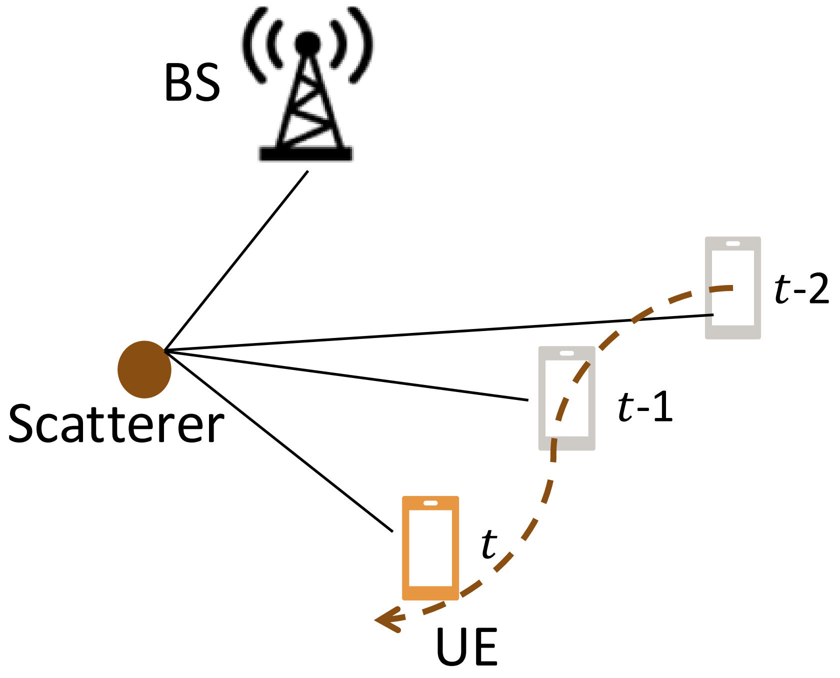
➢ Observation: D-MIMO provides distinct measurements from APs for the same landmark.

[1] Y. Xu, X. Cai, S. Willhammar, F. Tufvesson, "Experimental analysis of multipath characteristics in indoor distributed massive MIMO channels," *IEEE Antenna Wireless Propag. Lett.*, vol. 24, no. 11, pp. 3866-3870, Nov. 2025.

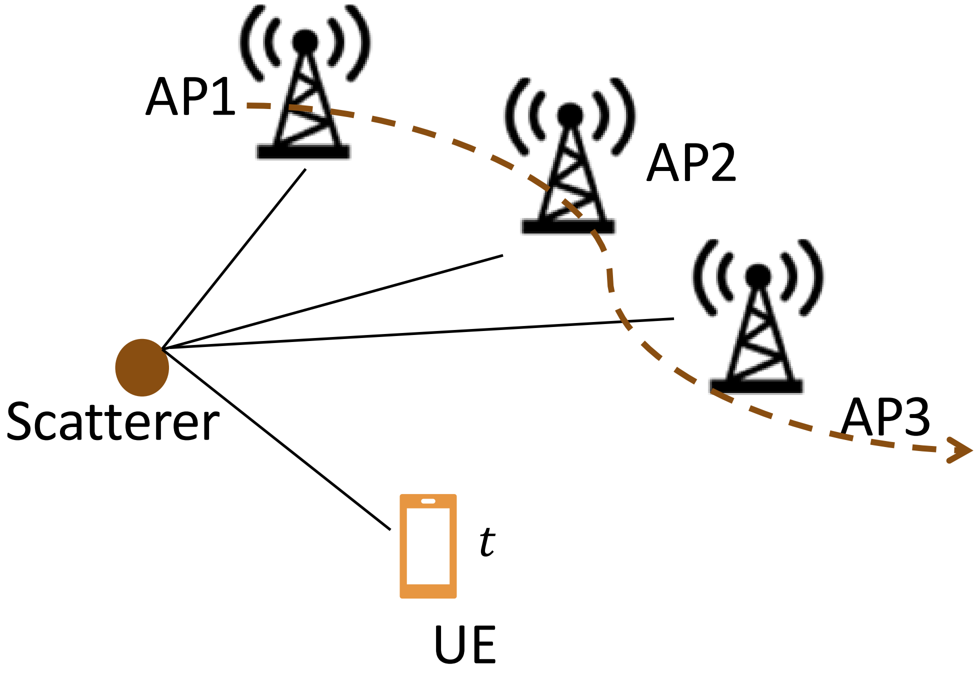
Bayesian filtering can be used even in single-snapshot mapping

- Bayesian filtering: **Prediction** → **Data Association** → **Update**

Spatial ~~Time~~ evolution



Multi-snapshot mapping, time-recursive



Single-snapshot mapping, spatial-recursive

Existing filtering-based methods

Ref.	Structure	Scenario	Reqiuired MPC parameters	Antenna setups
[1]	PHD-based	Co-located MIMO	Delay, angle of arrival, angle of departure	Arrays
[2][3]	PMBM-based	Co-located MIMO		
[4]	BP-based	Distributed MIMO		

*PHD: probability hypothesis density; PMBM: poisson multi-Bernoulli mixture; BP: belief propagation

- ➢ Existing methods often overlook distributed MIMO architectures, single-antenna UE settings, or both.

[1] H. Kim et al., "5G mmWave cooperative positioning and mapping using multimodel PHD filter and map Fusion," *IEEE Trans. Wireless Commun.*, vol. 19, no. 6, 2020, pp. 3782–3795.
[2] H. Kim, K. Granstr¨om, L. Svensson, S. Kim, and H. Wymeersch, "PMBM-based SLAM filters in 5G mmWave vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 71, no. 8, pp. 8646–8661, Aug. 2022.
[3] Y. Ge, O. Kaltiokallio, H. Kim, F. Jiang, J. Talvitie, M. Valkama, L. Svensson, S. Kim, and H. Wymeersch, "A computationally efficient EK-PMBM filter for bistatic mmWave radio SLAM," *IEEE J. Sel. Areas Commun.*, vol. 40, no. 7, pp. 2179–2192, Jul. 2022.
[4] X. Li, et al., "Adaptive multipath-based SLAM for distributed MIMO systems," *arXiv preprint*, https://arxiv.org/abs/2506.21798.

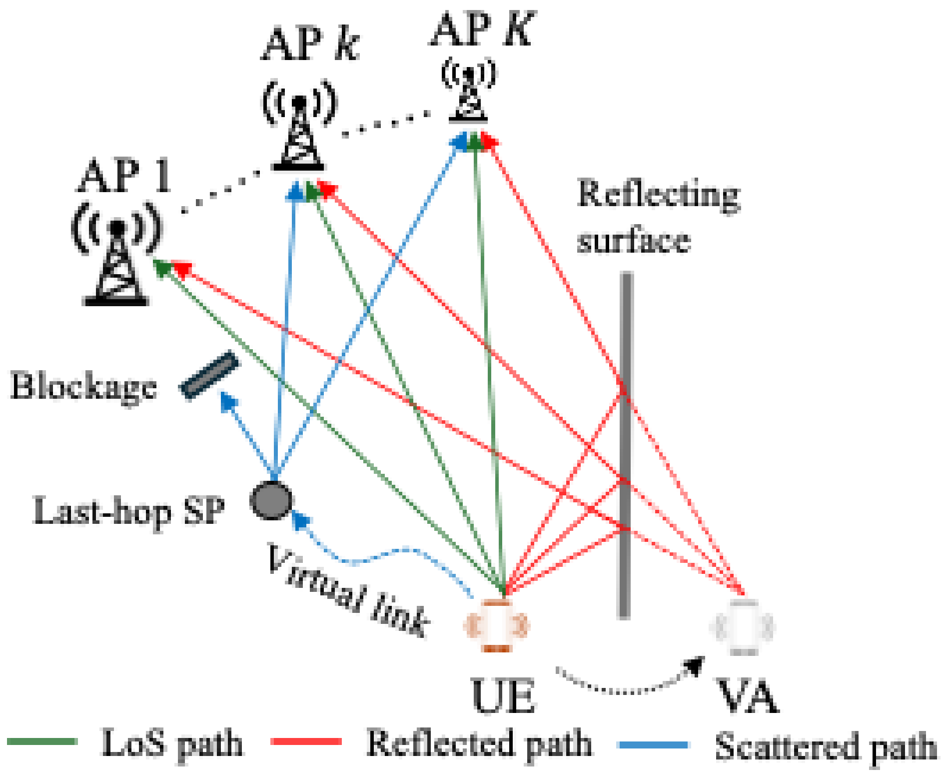
Our contributions

- Consider a more challenging single-snapshot mapping problem, including single-antenna UE setups.
- Design a spatial-recursive tracking filter with a unified multipath propagation model.
- Evaluate mapping performance through both simulations and real-world experiments.

Signal model

- K APs each equipped with an array, a single-antenna UE
- Received signals:

$$y_{k,m}(t) \\ = \sum_{l-1}^{L_{k,m}} \mathbf{c}^r\left(\phi^r_{l,k,m}\right)\mathbf{A}_{l,k,m}e^{-j2\pi v_{l,k,m}t}\boldsymbol{s}(t \\ - \tau_{l,k,m}) + \mathbf{n}_{k,m}$$



$\phi^r_{l,k,m}$: angle of arrival

$\tau_{l,k,m}$: delay

$v_{l,k,m}$: Doppler frequency

$\mathbf{A}_{l,k,m}$: polarization matrix

$\mathbf{n}_{k,m}$: additive Gaussian noise

$L_{k,m}$: Number of MPCs

$\mathbf{c}^r(\cdot)$: AP array response

$\mathbf{s}(t)$: transmitting signal

State and measurement models

- AP states: $\mathbf{x}^{\mathrm{AP}} = \left[\mathbf{p}^{\mathrm{AP}}, \mathbf{r}^{\mathrm{AP}}\right]^{\mathrm{T}}$
- UE states: $\mathbf{x}^{\mathrm{UE}} = [x^{\mathrm{UE}}, y^{\mathrm{UE}}]^{\mathrm{T}}$
- Unknown landmark states: $\mathbf{s} = [\boldsymbol{p}^{s}, d^{s}]^{\mathrm{T}}$

Residual propagation distance

- Measurement likelihood:

$$h\left(\boldsymbol{z}_{l,k,m}^{t} \middle| \mathbf{x}_{m}^{t}\right) = \mathcal{N}\left(\boldsymbol{z}_{l,k,m}^{t}; \xi(\mathbf{x}_{m}^{t}), \mathbf{W}^{t+1}\right)$$

$\mathbf{W}^{t+1}$: measurement noise covariance

$\xi(\cdot)$: measurement model: $\begin{bmatrix} \tau \\ \phi \end{bmatrix} = \begin{bmatrix} \frac{1}{c}\left\|\boldsymbol{p}^{s} - \boldsymbol{p}^{\mathrm{AP}}\right\|_{\mathrm{F}} + d^{s} \\ \arctan(\frac{y^{s}}{x^{s}}) \end{bmatrix}$

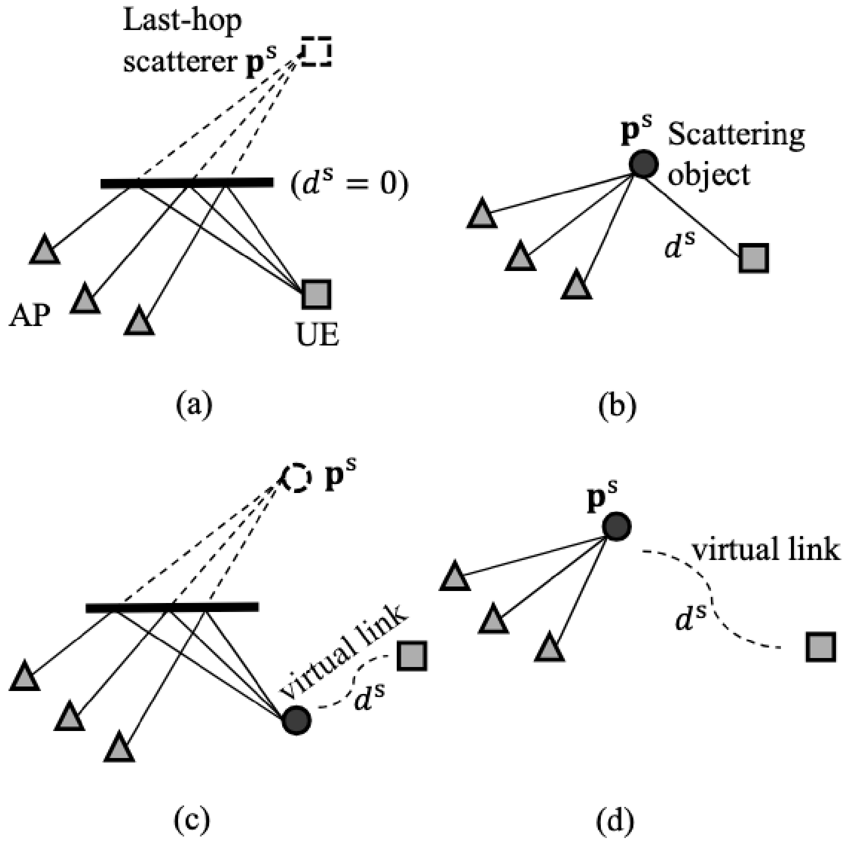
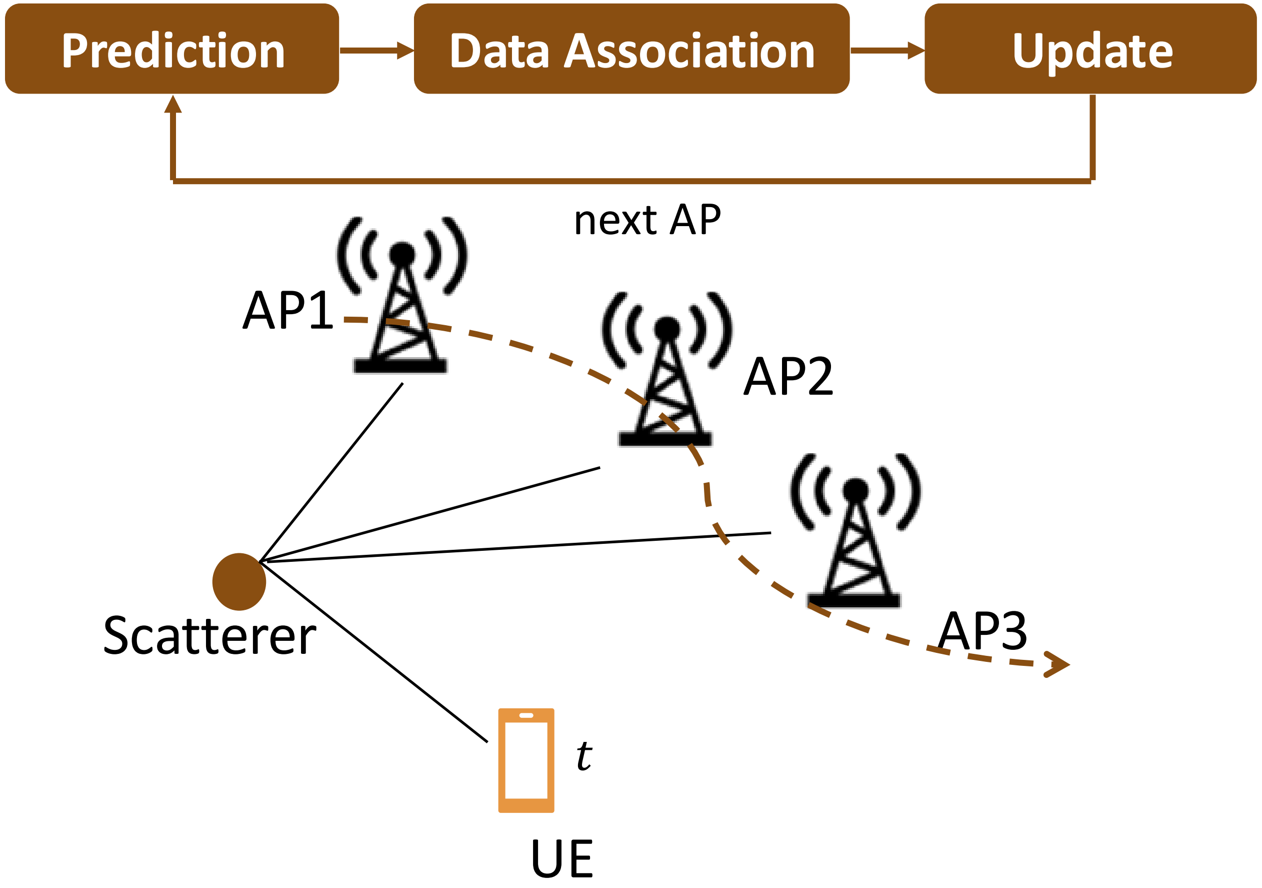


Fig. 1. MPCs with various propagation mechanisms.

By introducing d^{s}, different MPCs are characterized with the same model.

Bayesian filtering can be used even in single-snapshot mapping

- Target: to estimate the unknown landmark state $\mathbf{s} = [\boldsymbol{p}^{\mathrm{s}}, d^{s}]^{\mathrm{T}}$, given the prior $\mathbf{x}^{\mathrm{AP}}$.
- Bayesian filtering:



Single-snapshot mapping, spatial-recursive

Filter design

➢ One representative filter: **Poisson multi-Bernoulli mixture filter**

- follows the random finite set (RFS) theory.
- Undetected landmarks are modeled with a Poisson RFS $\mathcal{X}^{\mathrm{U}}$:

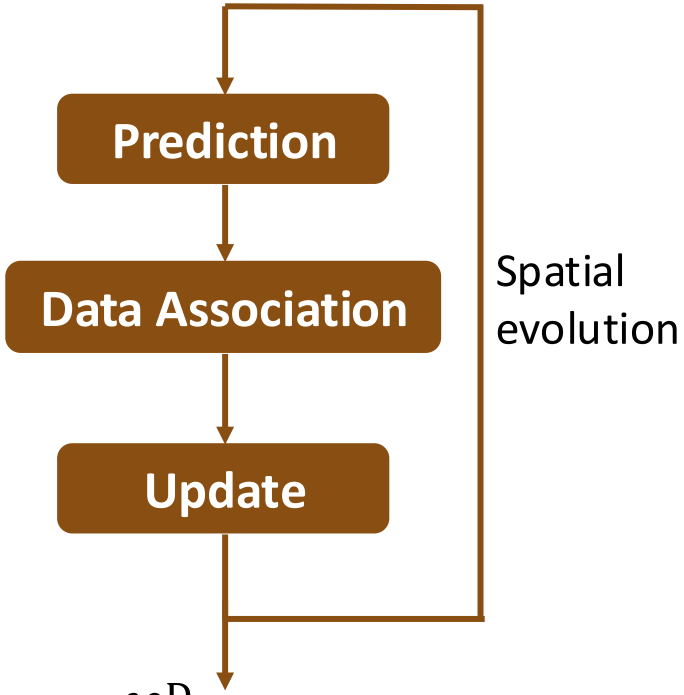
  Set prob. density $f^{\mathrm{P}}(\mathcal{X}^{\mathrm{U}}) = e^{-\int \lambda(\mathbf{s})d\mathbf{s}} \prod_{\mathbf{s}\in\mathcal{X}^{\mathrm{U}}} \lambda(\mathbf{s})$.

- Each detected landmark $\mathbf{s}_j$ are modeled with a Bernoulli RFS $\mathcal{X}_j^{\mathrm{D}}$:

$$f^{\mathrm{B}}(\mathcal{X}_j^{\mathrm{D}}) = \begin{cases} 1-r, & \mathcal{X}_j^{\mathrm{D}} = \emptyset \\ rp(\mathbf{s}_j), & \mathcal{X}_j^{\mathrm{D}} = \{\mathbf{s}_j\} \\ 0, & |\mathcal{X}_j^{\mathrm{D}}| > 1 \end{cases}$$

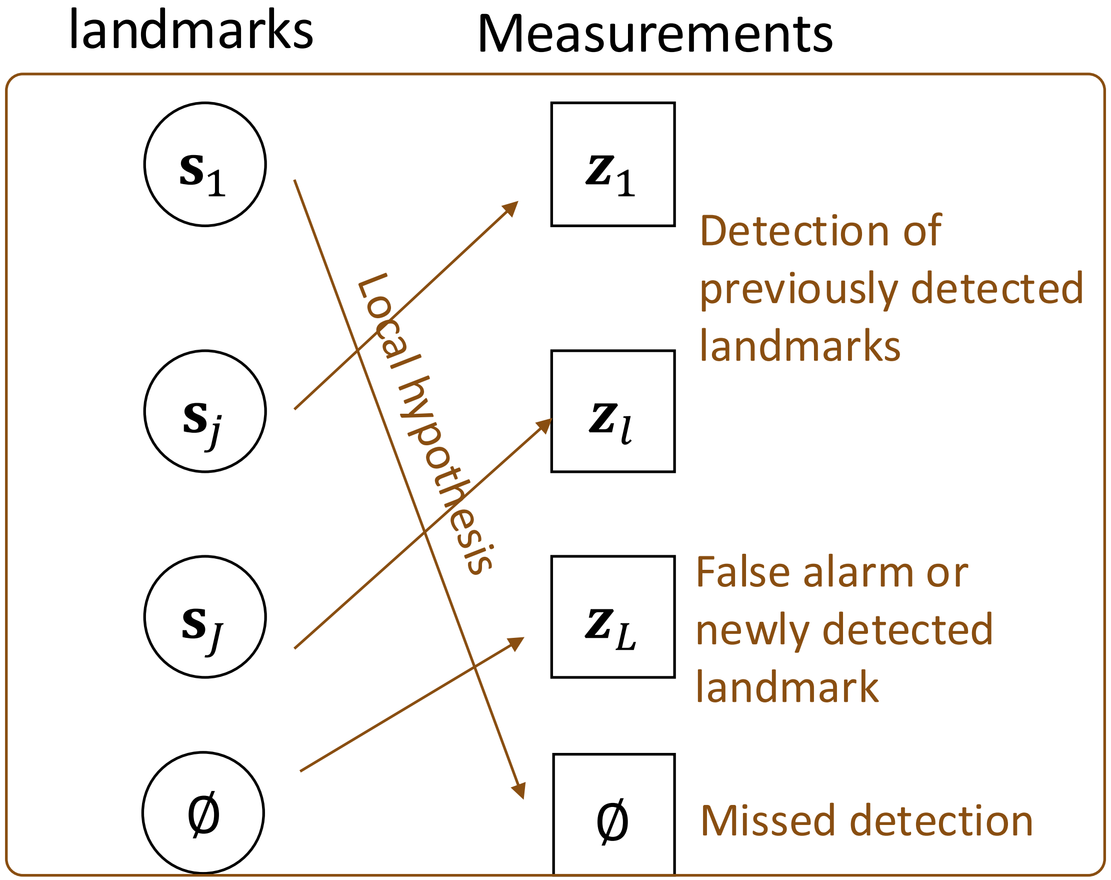
- All detected landmarks are modeled with a MBM RFS: $\mathcal{X}^{\mathrm{D}} = \mathcal{X}_1^{\mathrm{D}} \uplus \mathcal{X}_1^{\mathrm{D}} \uplus \cdots \uplus \mathcal{X}_1^{\mathrm{D}}$

$$f^{\mathrm{MBM}}(\mathcal{X}^{\mathrm{D}}) = \sum_{i=1}^{I} \sum_{\mathcal{X}=\mathcal{X}_1 \uplus \ldots \uplus \mathcal{X}_{J_{\mathrm{D}}}} \prod_{j=1}^{J_{\mathrm{D}}} g_{i,j} f_j^{\mathrm{B}}(\mathcal{X}_j),$$

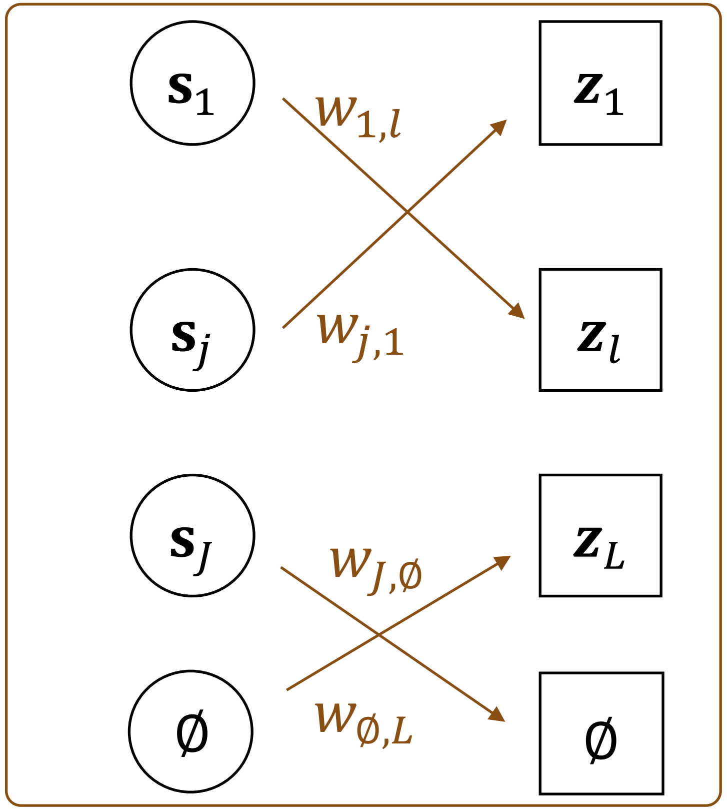


Data association exhibits uncertainty

- Perform spatial association by sequentially associating measurements from distributed APs with the landmarks.



Global Hypothesis 1



Global Hypothesis 2

Data association exhibits uncertainty

- Association weight is calculated according to each local hypothesis

- Detection of previously detected landmarks: $\mathbf{s}_j \Leftrightarrow \boldsymbol{z}_j$

$w_{j,l} = r_{j,k|k-1} \int p_{k|k-1}(\mathbf{s}_j) \Lambda(\boldsymbol{z}_j; \mathbf{s}_j) d\mathbf{s}_j$, where $\Lambda(\boldsymbol{z}_j; \mathbf{s}_j) = p_d g(\boldsymbol{z}_j; \mathbf{s}_j)$

p_d: detection probability; $g(\boldsymbol{z}_j; \mathbf{s}_j)$: measurement likelihood

- Detection of previously undetected landmarks: $\mathbf{s}_\emptyset \Leftrightarrow \boldsymbol{z}_l$

$$w_{\emptyset,l} = c(\boldsymbol{z}_l) + \int p_D g(\boldsymbol{z}_j; \mathbf{s}) f_b(\mathbf{s}) d\mathbf{s}$$

$g(\boldsymbol{z}_j; \mathbf{s})$: likelihood when $\mathbf{s}$ generates measurement $\boldsymbol{z}_l$

- Missed detection of previously detected landmarks:$\mathbf{s}_j \Leftrightarrow \boldsymbol{z}_\emptyset$

$$w_{j,\emptyset} = (1 - r_{j,k|k-1}) + r_{j,k|k-1}(1 - p_D)$$

- Global hypothesis is optimized through Murty's algorithm.

Update landmark state under each global hypothesis

- Detection of previously detected landmarks: $\mathbf{s}_j \Leftrightarrow \boldsymbol{z}_j$

$$r_{j,k|k} = 1, p_{j,k|k}(\mathbf{s}) = \frac{p_{k|k-1}(\mathbf{s}_j)\Lambda(\boldsymbol{z}_j;\mathbf{s}_j)}{\int p_{k|k-1}(\mathbf{s}_j)\Lambda(\boldsymbol{z}_j;\mathbf{s}_j)d\mathbf{s}_j}, g_{j,k|k}(\mathbf{s}) = g_{j,k|k-1}(\mathbf{s})r_{j,k|k}\int p_{k|k-1}(\mathbf{s}_j)\Lambda(\boldsymbol{z}_j;\mathbf{s}_j)d\mathbf{s}_j$$

- Missed Detection of previously undetected landmarks:

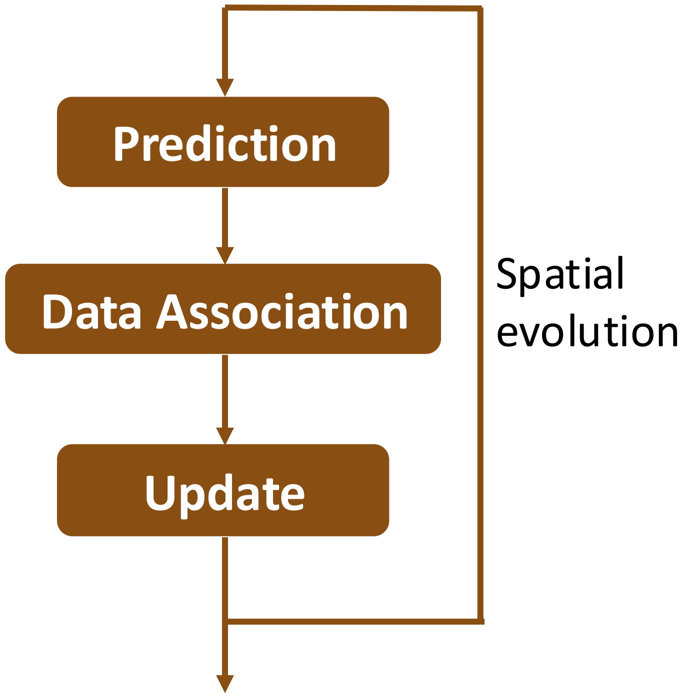
$$\lambda_{j,k|k}(\mathbf{s}) = (1-p_D)\lambda_{j,k|k}(\mathbf{s})$$

- Missed Detection of previously detected landmarks:

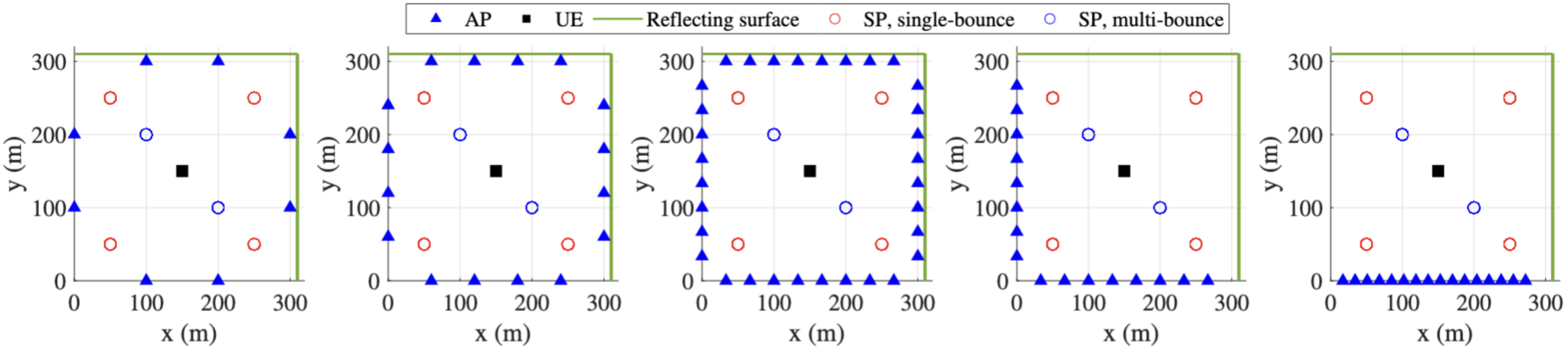
$$r_{j,k|k} = \frac{(1-p_D)r_{j,k|k-1}}{1-p_D r_{j,k|k-1}}, p_{j,k|k}(\mathbf{s}) = p_{j,k|k-1}(\mathbf{s}), g_{j,k|k}(\mathbf{s}) = g_{j,k|k-1}(1-p_D)$$

- Detection of previously undetected landmarks:

$$r_{j,k|k} = \frac{\int p_D g(\boldsymbol{z}_j;\mathbf{s})f_b(\mathbf{s})d\mathbf{s}}{c(\boldsymbol{z}_l)+\int p_D g(\boldsymbol{z}_j;\mathbf{s})f_b(\mathbf{s})d\mathbf{s}}, p_{j,k|k}(\mathbf{s}) = \frac{p_D g(\boldsymbol{z}_j;\mathbf{s})f_b(\mathbf{s})}{\int p_D g(\boldsymbol{z}_j;\mathbf{s})f_b(\mathbf{s})d\mathbf{s}}$$



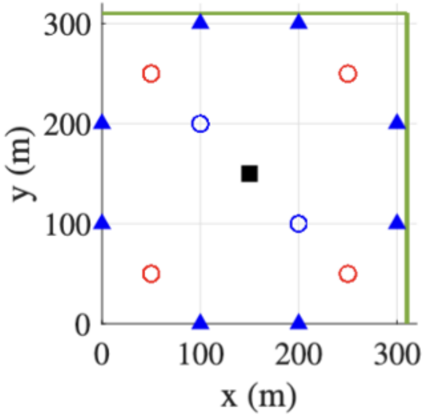
Performance evaluation through simulations



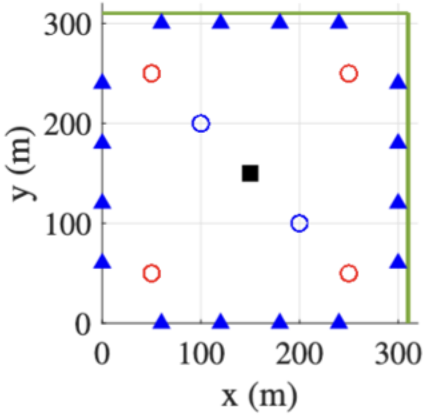
- Different AP density and spatial distributions.
- 2 reflected paths, 4 single-bounce and 2 multi-bounce scattered paths.

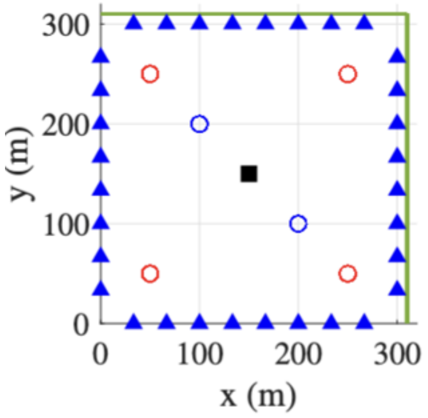
Higher AP density leads to better mapping performance

AP density K=8

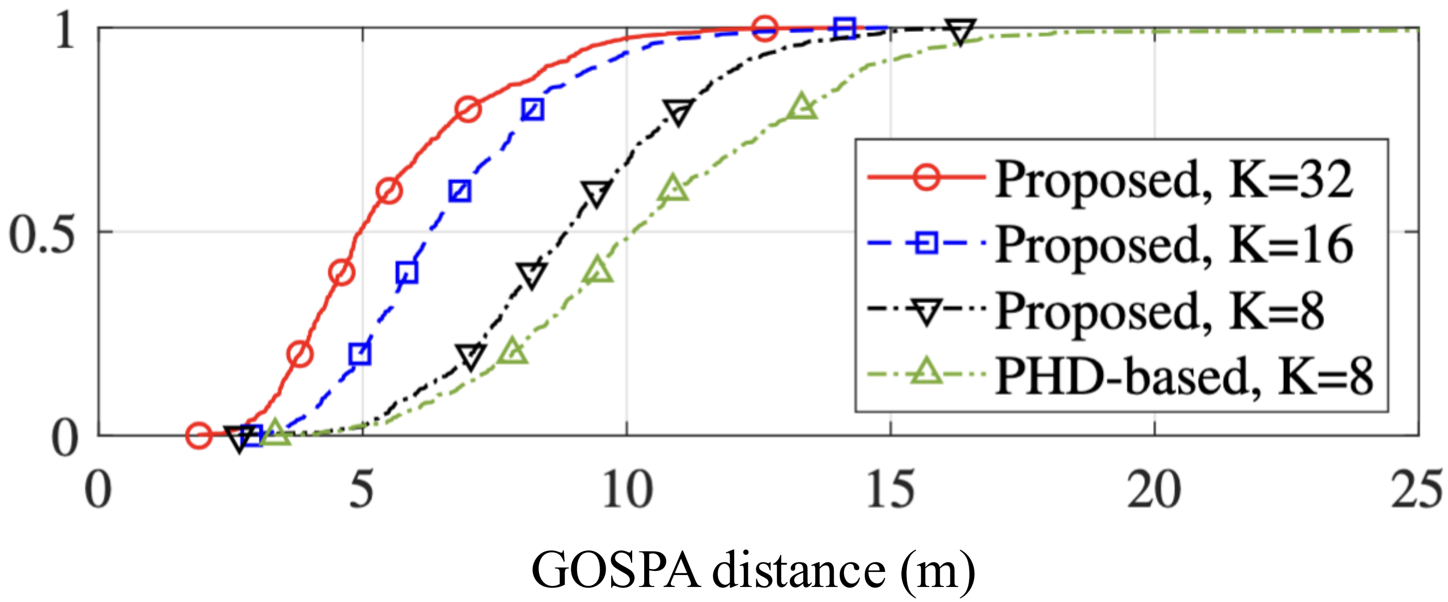


K=16





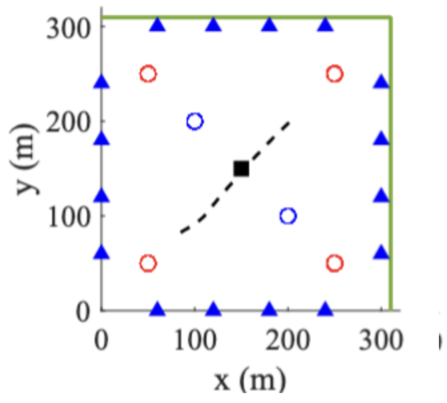
K=32



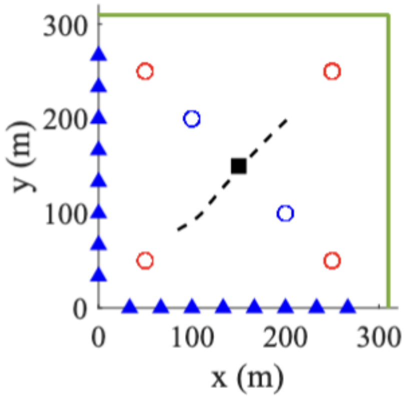
CDFs of GOSPAs [1] achieved by the proposed filter and with the PHD-based filter (benchmark)

[1] A. S. Rahmathullah, A. F. García-Fernández, and L. Svensson, "Generalized optimal sub-pattern assignment metric," in Proc. 20th IEEE Int. Conf. Inf. Fusion (Fusion), Jul. 2017, pp. 1–8.

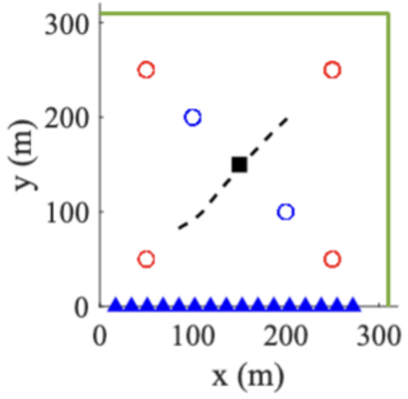
AP spatial distribution affects the mapping performance



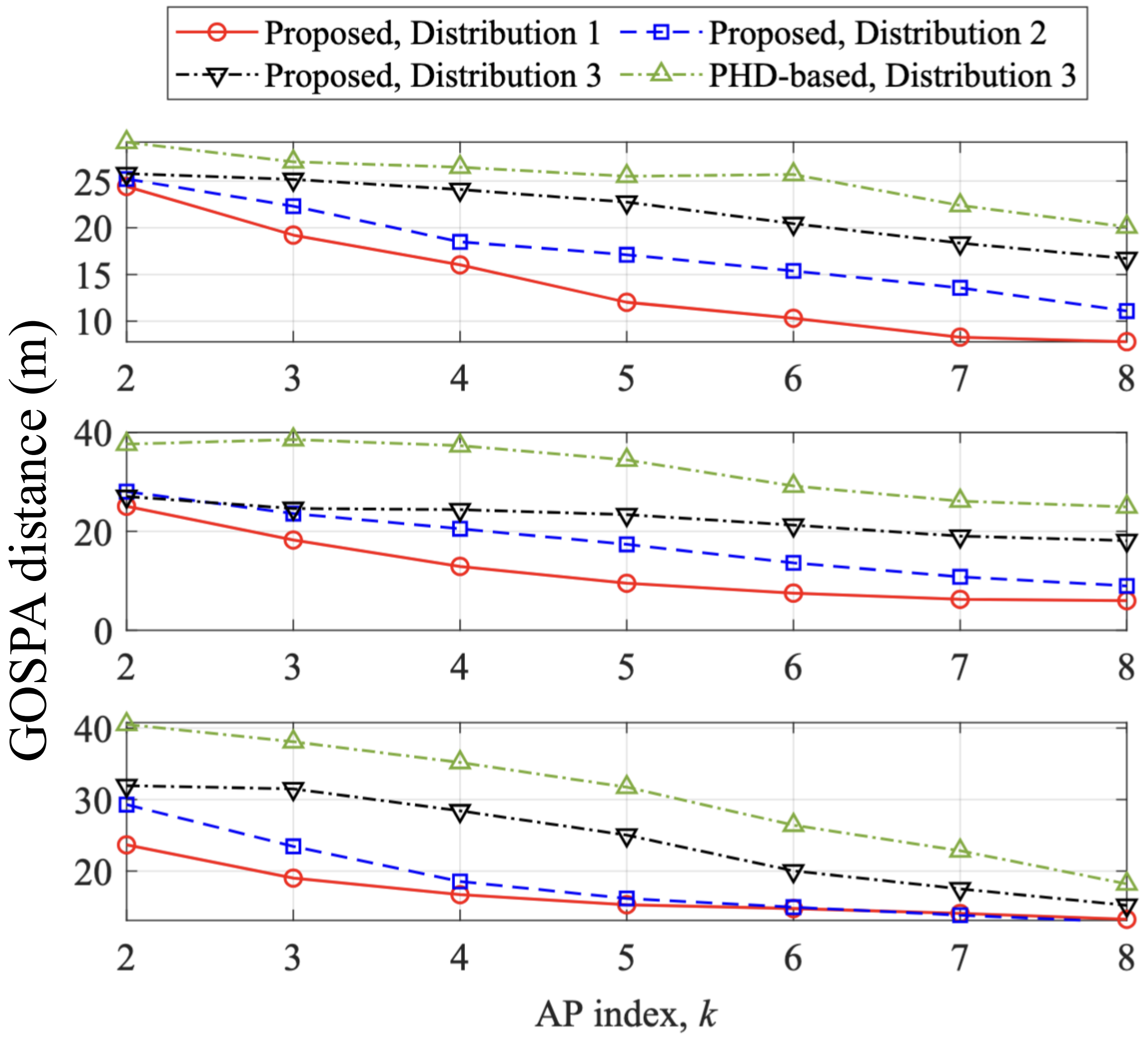
AP distribution 1



Distribution 2

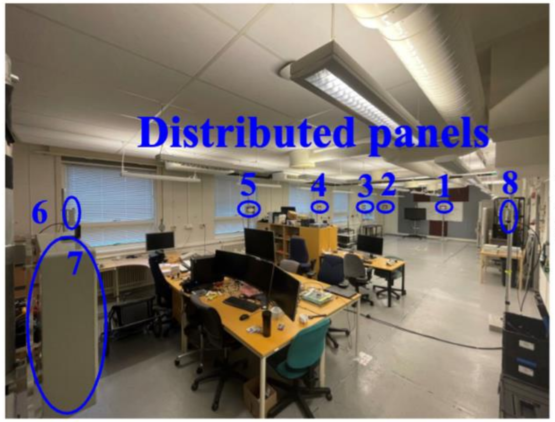


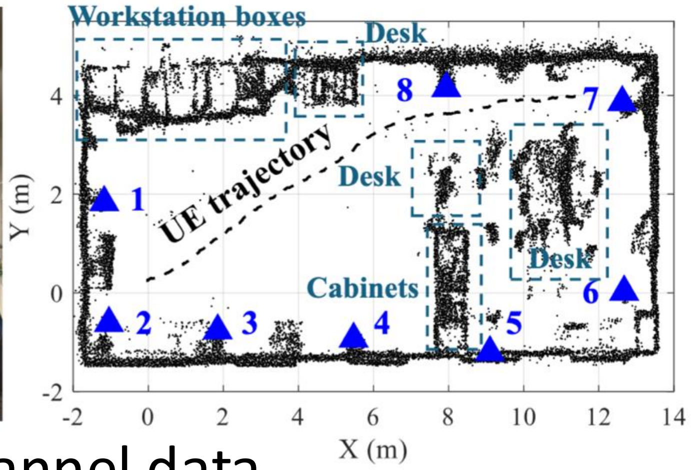
Distribution 3



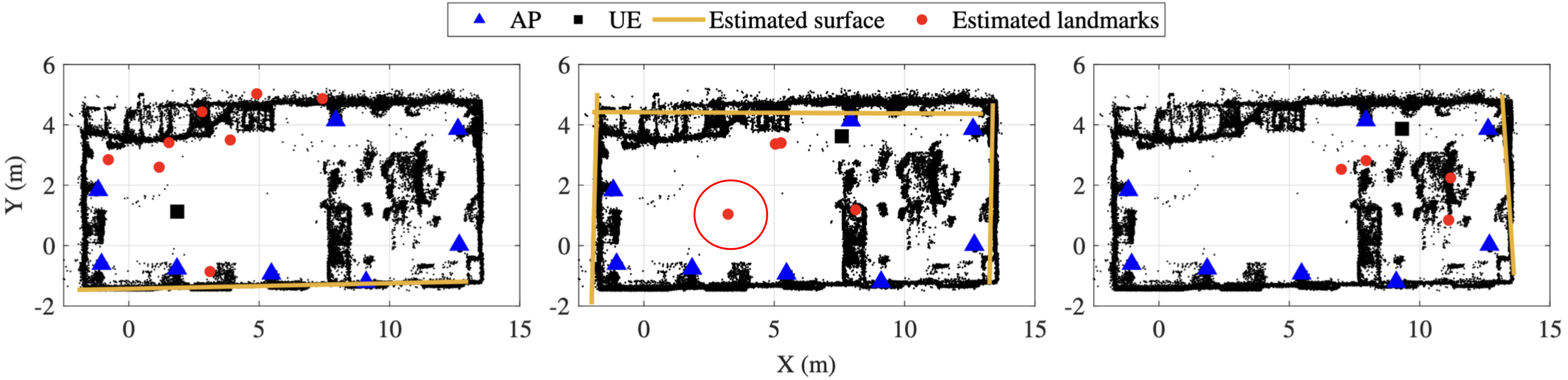
Mapping results consistent with physical environments

- Real-world distributed MIMO channels





- Performance evaluation with realistic channel data



LUND UNIVERSITY