Recent Advances in Bistatic Radio-based Simultaneous Localization and Mapping

6G Test Network Finland Workshop

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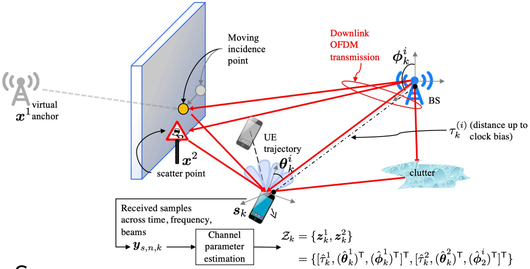
September 26, 2024

Quick Recap of Bistatic Radio-SLAM

- Radio-based bistatic SLAM:
  - UE position, orientation, clock offset/drift
  - Localize interaction points of NLoS paths
  - Technical basis comes from the ability to measure propagation delays and angles
- Importance of Radio-SLAM:
  - Improves localization accuracy
  - Possible to localize the UE in the absence of LoS
  - Dependence on infrastructure can be reduced enabling localization even using a single transmission from one BS
- Mainstream Radio-SLAM approaches:
  - Filtering-based solutions that recursively estimate the joint state of the UE and map by sequential processing
  - Snapshot approaches that solve the SLAM problem for a single UE location without any prior information nor kinematic models



Experimental mmWave Measurements

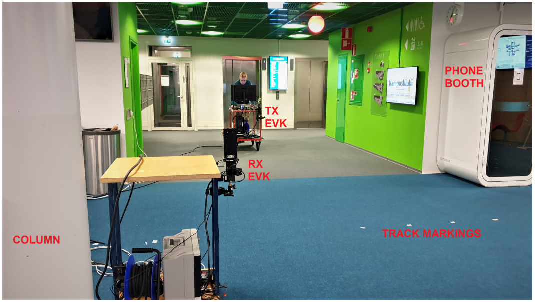


Table 1: Measurement parameters

Center frequency	60 GHz
Bandwidth	400 MHz
SCS	120 kHz
Antenna array size	16 x 4
3dB beamwidth	≈10 degrees
Signal type	PRS (DL)
PRS comb factor	2
PRS symbol per slot	1

- Stationary BS and moving UE. Both equipped with Sivers Semionductors 60 GHz beamforming EVKs allowing for electrical beamforming and beamsweaping
- Experimental mmWave measurements available at [1]

[1] E. Rastorgueva-Foi, O. Kaltiokallio, Y. Ge, M. Turunen, J. Talvitie, B. Tan, M.F. Keskin, H. Wymeersch, and M. Valkama, April 26, 2024, "Millimeter-Wave Radio SLAM: 60 GHz Indoor Sensing Dataset", IEEE Dataport, doi: https://dx.doi.org/10.21227/xskh-dk87.

Snapshot SLAM (2D/azimuth domain)

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- The BS location $\mathbf{p}_{\mathsf{BS}} \in \mathbb{R}^2$ and orientation $\alpha_{\mathsf{BS}} \in [-\pi, \pi]$ are assumed known.
- The measurement set is denoted using

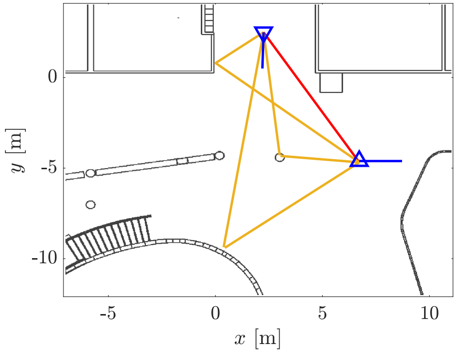
$$\mathcal{Z} = \{\mathbf{z}_0, \mathbf{z}_1 \ldots, \mathbf{z}_N\}$$

  in which $\mathbf{z}_i = [\tau_i,\ \phi_i,\ \theta_i]^\top$ denotes the channel parameters of the ith path, estimated using the method presented in [2].
- The associated indices are $\mathcal{I} = \{0, 1, \ldots, N\}$.
- Using $\mathcal{Z}$, the aim is to estimate the UE state,

$$\mathbf{x} = [\mathbf{p}_{\mathsf{UE}}^\top,\ \alpha_{\mathsf{UE}},\ b_{\mathsf{UE}}]^\top \in \mathbb{R}^4,$$

  and landmark locations,

$$\mathbf{p}_i \in \mathbb{R}^2\ \forall i \in \mathcal{I}.$$



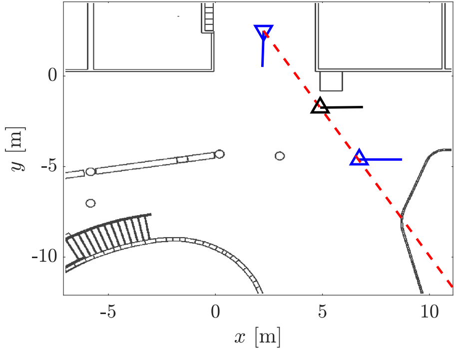
[2] E. Rastorgueva-Foi, O. Kaltiokallio, Y. Ge, M. Turunen, J. Talvitie, B. Tan, M.F. Keskin, H. Wymeersch, and M. Valkama. *"Millimeter-Wave Radio SLAM: End-to-End Processing Methods and Experimental Validation,"*, in IEEE Journal on Selected Areas in Communications, vol. 42, no. 9, pp. 2550-2567, Sept. 2024

Snapshot SLAM

- Using the LoS component $i = 0$, the UE orientation is given by

$$\hat{\alpha}_{\mathsf{UE}} = \mathrm{atan2}(y, x), \tag{1}$$

where $[x,\ y]^\top = -\mathbf{R}(-\theta_0)\mathbf{u}_0$ and in which $\mathbf{R}$ denotes a counterclockwise rotation matrix, θ_0 is the AoA and $\mathbf{u}_0$ a unit vector along the AoD.



Snapshot SLAM

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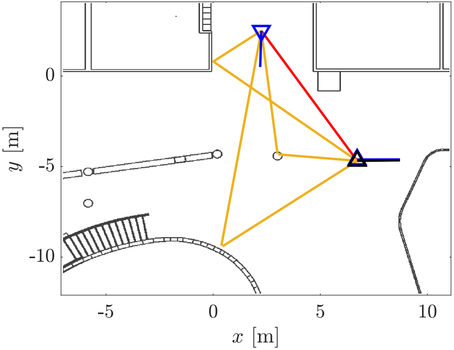
- AoD and AoA can be represented by unit vectors $\mathbf{u}_i$ and $\mathbf{v}_i$, allowing to express the UE position as:

$$\mathbf{p}_{\text{UE}} = \mathbf{p}_{\text{BS}} + d_i \gamma_i \mathbf{u}_i - d_i(1 - \gamma_i)\mathbf{v}_i \tag{2}$$

where $d_i = c(\tau_i - b_{\text{UE}})$ and $\gamma_i \in [0, 1]$ is unknown. From (2), a cost for $\mathbf{x}$ can be derived

$$J(\mathbf{x}) = \sum_{i \in \mathcal{I}} \eta_i J_i(\mathbf{x}) \tag{3}$$

and $J(\mathbf{x})$ can be minimized wrt. $\mathbf{x}$ in closed-form to obtain $\hat{\mathbf{x}}$.



Snapshot SLAM

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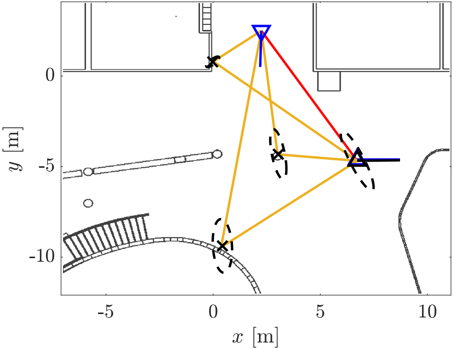
and $J(\mathbf{x})$ can be minimized wrt. $\mathbf{x}$ in closed-form to obtain $\hat{\mathbf{x}}$.

- Given $\hat{\mathbf{x}}$, the landmark locations can be estimated for every NLoS propagation path $i = 1, 2, \ldots, N$, independently, e.g., by solving the following nonlinear optimization problem

$$\hat{\mathbf{p}}_i = \underset{\mathbf{p}_i}{\text{minimize}}\ (\mathbf{z}_i - \mathbf{h}(\mathbf{x}, \mathbf{p}_i))^\top \boldsymbol{\Sigma}_i^{-1}(\mathbf{z}_i - \mathbf{h}(\mathbf{x}, \mathbf{p}_i)), \tag{4}$$

where $\mathbf{h}(\mathbf{x}, \mathbf{p}_i)$ and $\boldsymbol{\Sigma}_i$ denote the mean and covariance of the likelihood function.

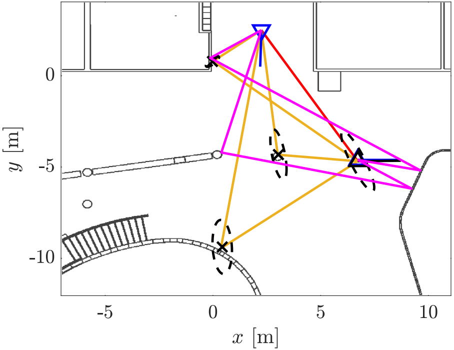


Multi-bounce Signals

- For an m-bounce signal, the UE position is given by:

$$\mathbf{p}_{\text{UE}} = \mathbf{p}_{\text{BS}} + d_i\gamma_i^1\mathbf{u}_i - d_i\gamma_i^m\mathbf{v}_i + \sum_{j=1}^{m-1}(\mathbf{p}_i^{j+1} - \mathbf{p}_i^j), \quad (5)$$

  where $\gamma_i^1 \in [0,1]$ and $\gamma_i^m \in [0,1]$ are unknown and they represent the fraction of the propagation distance along $\mathbf{u}_i$ and $\mathbf{v}_i$, respectively, and $\gamma_i^1 + \gamma_i^m \leq 1$.
- Since the terms in the sum are unknown, (5) does not admit a unique solution and therefore, exploiting multi-bounce signals for SLAM is very challenging.
- Multi-bounce signals will cause significant SLAM performance degradation since the multi-bounce and single-bounce models have a mismatch.
- To overcome this deficit, we can try to identify multi-bounce signals and discard them from $\mathcal{Z}$ when solving the SLAM problem [3].



[3] O. Kaltiokallio, E. Rastorgueva-Foi, J. Talvitie, Y. Ge, H. Wymeersch, and M. Valkama. *"Robust snapshot radio SLAM"*, submitted to IEEE TVT 2024. [Online]. Available: https://arxiv.org/abs/2404.10291

Snapshot SLAM with Outliers

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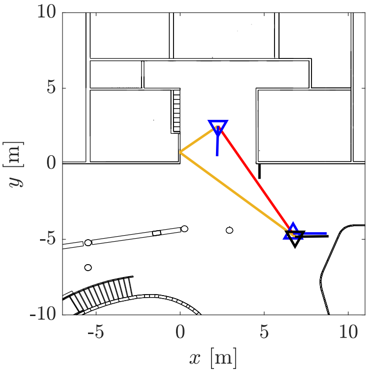
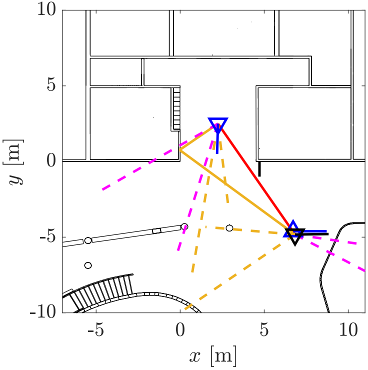
Minimal set	$J_0(\mathbf{x}, \mathcal{I})$	$J_1(\mathbf{x}, \mathcal{I})$	$J_2(\mathbf{x}, \mathcal{I})$	$J_3(\mathbf{x}, \mathcal{I})$	$J_4(\mathbf{x}, \mathcal{I})$	$J_5(\mathbf{x}, \mathcal{I})$	$J(\mathbf{x}, \mathcal{I})$
$\mathcal{I} = \{0, 1\}$							



1. Use a *minimal subset* (e.g. $\mathcal{I} = \{0, 1\}$) of the channel parameter estimates to compute an initial solution

Snapshot SLAM with Outliers

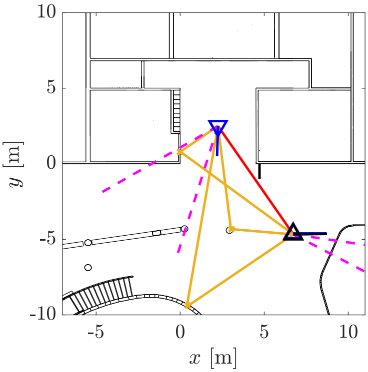
Minimal set	$J_0(\mathbf{x}, \mathcal{I})$	$J_1(\mathbf{x}, \mathcal{I})$	$J_2(\mathbf{x}, \mathcal{I})$	$J_3(\mathbf{x}, \mathcal{I})$	$J_4(\mathbf{x}, \mathcal{I})$	$J_5(\mathbf{x}, \mathcal{I})$	$J(\mathbf{x}, \mathcal{I})$
$\mathcal{I} = \{0, 1\}$	2.1e-27	6.5e-29	5.6e-07	1.4e-07	4.2e-03	1.0e-03	



1. Use a *minimal subset* (e.g. $\mathcal{I} = \{0, 1\}$) of the channel parameter estimates to compute an initial solution.
2. According to the principles of RANSAC, the channel parameter estimates are partitioned into a *set of inliers* and a *set of outliers* based on the initial solution.

Snapshot SLAM with Outliers

Minimal set	$J_0(\mathbf{x}, \mathcal{I})$	$J_1(\mathbf{x}, \mathcal{I})$	$J_2(\mathbf{x}, \mathcal{I})$	$J_3(\mathbf{x}, \mathcal{I})$	$J_4(\mathbf{x}, \mathcal{I})$	$J_5(\mathbf{x}, \mathcal{I})$	$J(\mathbf{x}, \mathcal{I})$
$\mathcal{I} = \{0, 1\}$	2.1e-27	6.5e-29	5.6e-07	1.4e-07	4.2e-03	1.0e-03	**2.15e-06**



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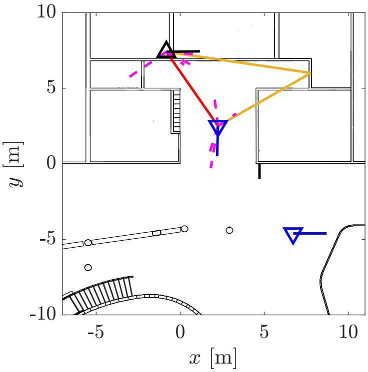
2. According to the principles of RANSAC, the channel parameter estimates are partitioned into a *set of inliers* and a *set of outliers* based on the initial solution.
3. The problem is re-solved using the inlier set and a cost for the solution is computed, denoted by $J(\mathbf{x}, \mathcal{I})$.

Snapshot SLAM with Outliers

Minimal set	$J_0(\mathbf{x}, \mathcal{I})$	$J_1(\mathbf{x}, \mathcal{I})$	$J_2(\mathbf{x}, \mathcal{I})$	$J_3(\mathbf{x}, \mathcal{I})$	$J_4(\mathbf{x}, \mathcal{I})$	$J_5(\mathbf{x}, \mathcal{I})$	$J(\mathbf{x}, \mathcal{I})$
$\mathcal{I} = \{0, 5\}$	2.8e-28	1.4e-03	1.4e-03	1.7e-04	5.6e-05	2.6e-29	**1.64e-05**



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4. The above three steps are performed for all minimal subsets...

Snapshot SLAM with Outliers

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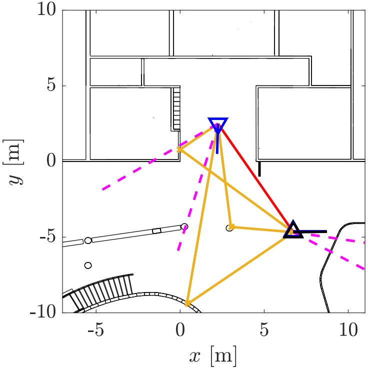
Minimal set	$J_0(\mathbf{x}, \mathcal{I})$	$J_1(\mathbf{x}, \mathcal{I})$	$J_2(\mathbf{x}, \mathcal{I})$	$J_3(\mathbf{x}, \mathcal{I})$	$J_4(\mathbf{x}, \mathcal{I})$	$J_5(\mathbf{x}, \mathcal{I})$	$J(\mathbf{x}, \mathcal{I})$
$\mathcal{I} = \{0, 1\}$	2.1e-27	6.5e-29	5.6e-07	1.4e-07	4.2e-03	1.0e-03	**2.15e-06**
$\mathcal{I} = \{0, 2\}$	3.6e-28	5.4e-07	1.3e-29	1.1e-08	4.0e-03	9.7e-04	**2.15e-06**
$\mathcal{I} = \{0, 3\}$	4.9e-27	1.1e-06	9.1e-08	5.7e-30	3.9e-03	9.5e-04	**2.15e-06**
$\mathcal{I} = \{0, 4\}$	7.9e-31	1.1e-03	1.1e-03	1.4e-04	1.9e-30	1.1e-05	**1.58e-05**
$\mathcal{I} = \{0, 5\}$	2.8e-28	1.4e-03	1.4e-03	1.7e-04	5.6e-05	2.6e-29	**1.64e-05**



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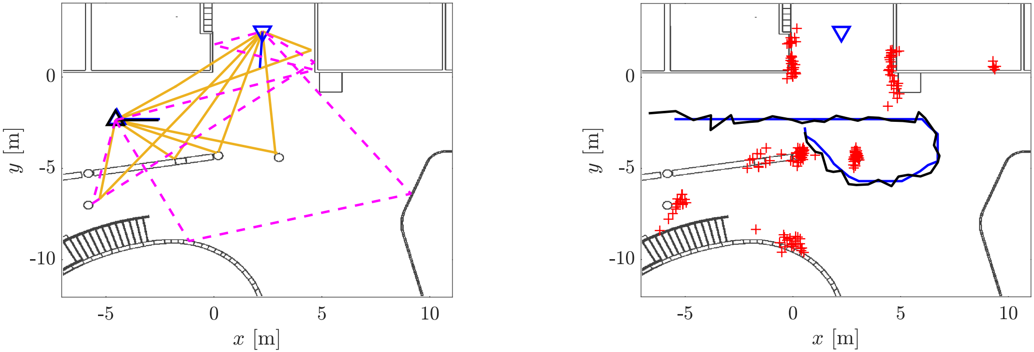
3. The problem is re-solved using the inlier set and a cost for the solution is computed, denoted by $J(\mathbf{x}, \mathcal{I})$.
4. The above three steps are performed for all minimal subsets and the solution is the one that minimizes $J(\mathbf{x}, \mathcal{I})$.

Robust Snapshot SLAM in mixed LoS/NLoS conditions [3]



Condition	Pos. [m]	Head. [deg]	Clk. [ns]	Time [ms]
LoS (32/45)	0.29	1.95	1.05	0.02
NLoS (13/45)	0.49	2.27	2.13	10.40

[3] O. Kaltiokallio, E. Rastorgueva-Foi, J. Talvitie, Y. Ge, H. Wymeersch, and M. Valkama. *"Robust snapshot radio SLAM"*, submitted to IEEE TVT 2024. [Online]. Available: https://arxiv.org/abs/2404.10291

Beyond SLAM – Mapping with Double-bounce Signals [4]

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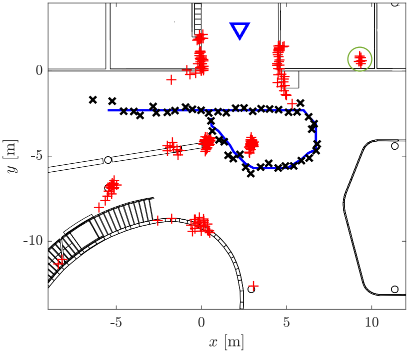
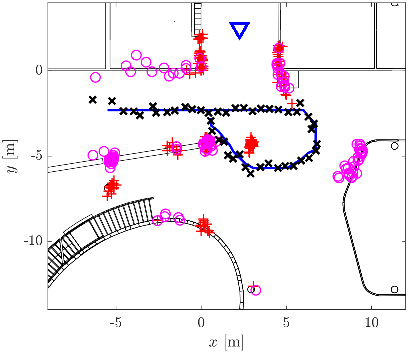
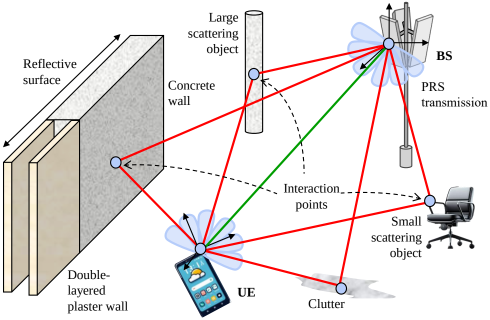


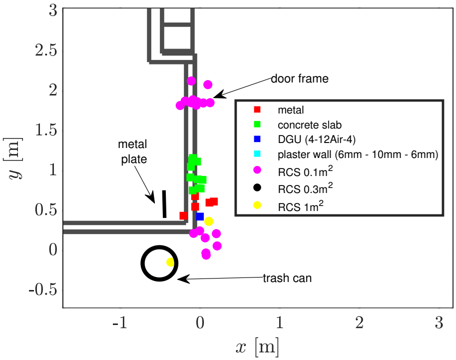


Signal type	Single-bounce	Double-bounce
LoS	32 (7.8 %)	32 (7.8 %)
1st order	231 (56.3 %)	198 (48.3 %)
2nd order	-	112 (27.3 %)
Outliers	147 (35.9 %)	68 (16.6 %)

[4] O. Kaltiokallio, Y. Ge, J. Talvitie, E. Rastorgueva-Foi, H. Wymeersch, and M. Valkama. *"Bistatic mmWave Mapping in Obstructed Environments Using Double-bounce Signals"*, 25th IEEE International Workshop on Signal Processing Advances in Wireless Communications, Sept. 2024.

Beyond SLAM – Materials Characterization [5]





[5] A. Karttunen, J. Talvitie, O. Kaltiokallio, E. Rastorgueva-Foi, and M. Valkama. *"Towards Semantic Radio SLAM with Landmark Feature Extraction in mmWave Networks"*, submitted to 5th IEEEInternational Symposium on Joint Communications & Sensing.

Conclusions

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- Radio-based bistatic SLAM enables accurate localization using a single transmission from just one BS even in the absence of LoS.
- It is important to identify multi-bounce signals so that they can be either discarded or exploited.
- Correctly utilizing double-bounce signals they can be turned from foe to friend.
- Interesting research directions towards semantic multi-bounce radio SLAM.
- Not a one man show, special thanks to:

  Jukka Talvitie, Elizaveta Rastorgueva-Foi, Matias Turunen, Aki Karttunen, Bo Tan, Mikko Valkama, Yu Ge, Musa Furkan Keskin, Henk Wymeersch