ELLIT Workshop

Joint Unsourced Random Access, Channel Estimation, and User Localization in Cell-Free User-Centric Networks

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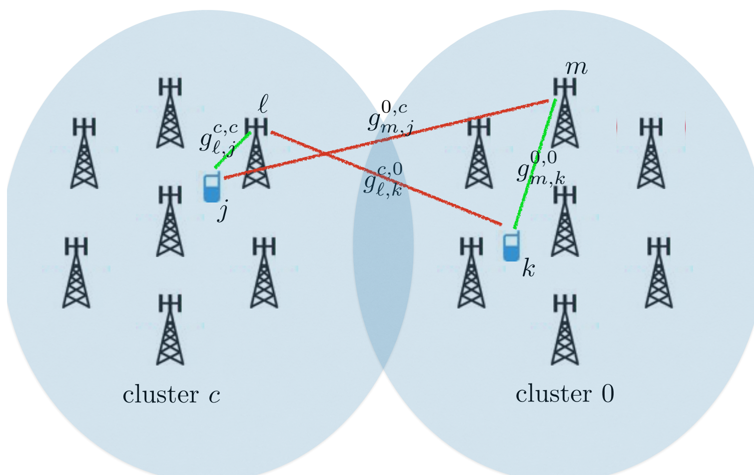
Linköping University, April 21-23, 2026

Joint Processing of Distributed Antennas

- [Wyner, TIT 1994]: centralized processing of all antennas in the uplink, Vector Gaussian MAC, capacity region was already known.
- [GC, Shamai, TIT 2003 – Weingarten, Steinberg, Shamai, TIT 2006]: Vector Gaussian BC, sum capacity and capacity region, in the downlink.
- Some past attempts: Coordinated MultiPoint (CoMP) .... not so successful, per-site (non-cooperative) massive MIMO has taken over the scene...
- Some successes: C-RAN, distributed antenna systems with joint processing, virtualization of the PHY/MAC in the CP.

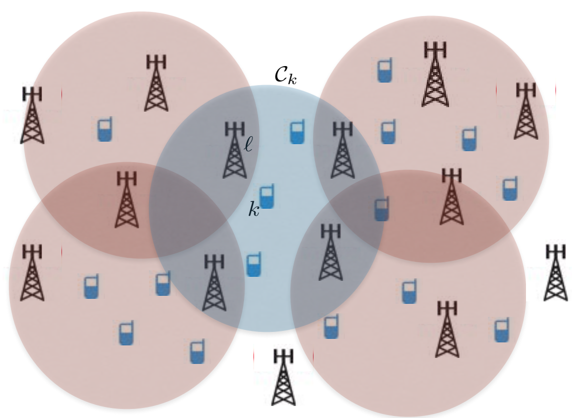


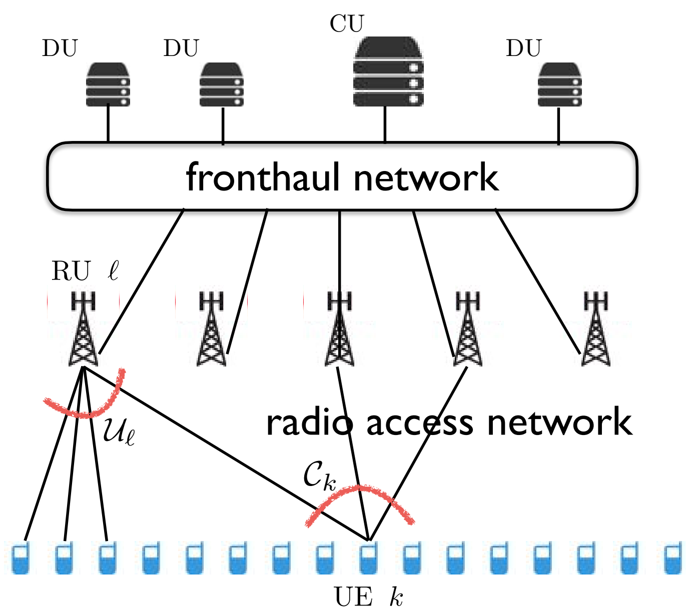
Cell-Free User-Centric Wireless Networks (1)

- Expected to become central in 6G systems operating in FR3 (7-24 GHz).
- Ultra-dense scenarios: campus networks, super-high spectral efficiency ... e.g. a sport arena with 10,000 users, on a 20-60 MHz bandwidth, served by 20 RUs with 10 antennas each, achieving ~ 50 bit/s/Hz per 10×10 m^2.
- Improved coverage scenarios: moving from FR1 (5G) to FR3 (6G), the traditional cells "shrink" and "holes" most be covered by RU cooperation.

Cell-Free User-Centric Wireless Networks (2)

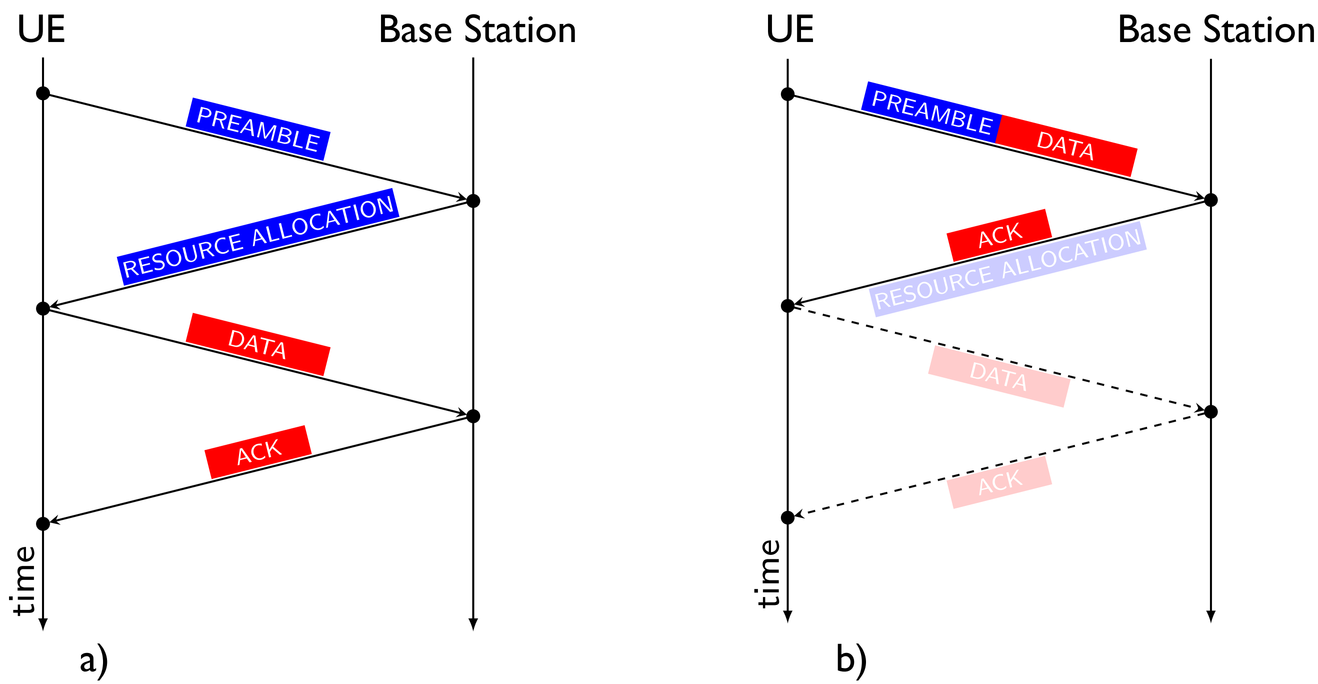
- Each UE is served by a user-centric cluster of RUs; each RU participates in multiple user-centric clusters.
- RUs are connected with DUs via a flexible fronthaul network, and implement the user-centric cluster processors (PHY layer) as SDVNF.
- A CU implements higher level centralized functions.
- Scalability: as the coverage area $A \to \infty$, with given RU density λ_a, DU density λ_d, and UE density λ_u, the load of the fronthaul at any node and the computational load at any processor remain finite.



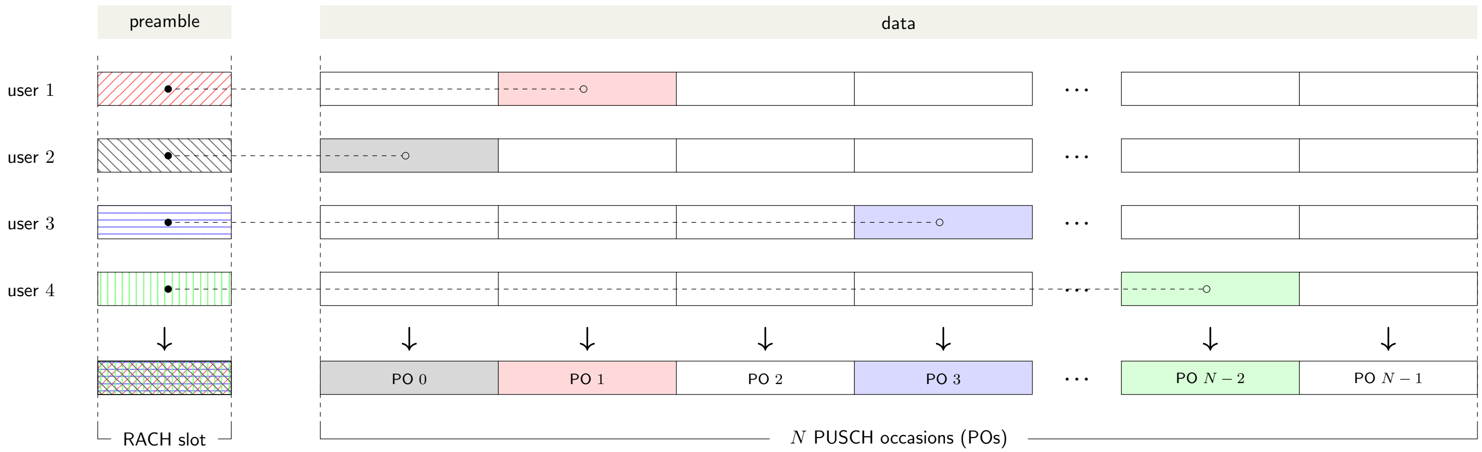


Random Access

- RACH: it is used to allow “idle users” to access the network and possibly request resources.
- To allow sporadic low-latency communications, 3GPP has specified a “2-step RACH” scheme (b) beyond the traditional “4-step RACH” (a).
- The 3GPP 2-step RACH fits very well the unsourced Random Access (uRA) model [Polyanskiy, 2017].

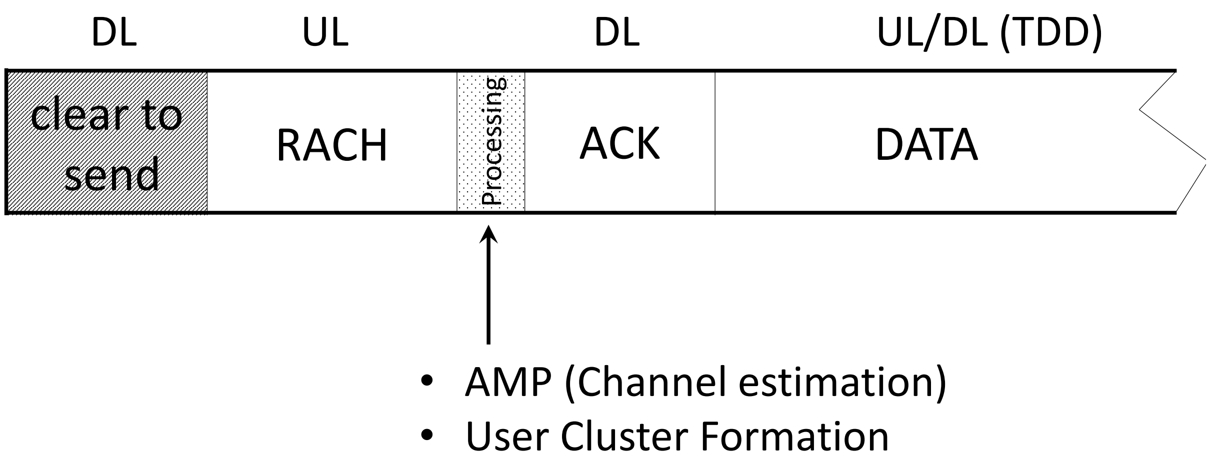


2-Step RACH



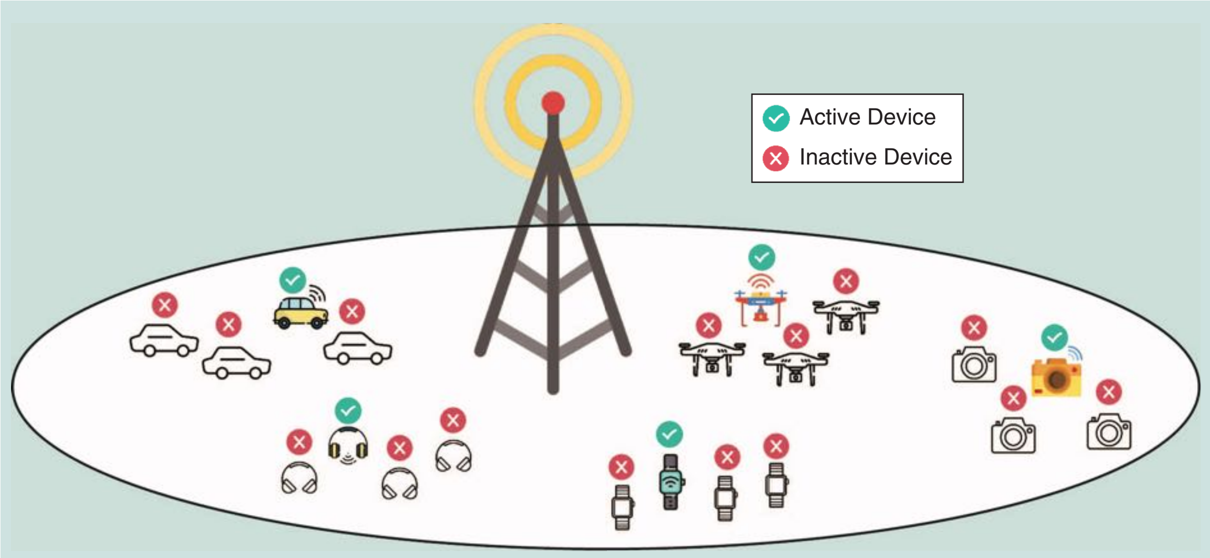
- Pilot + Data approach.
- uRA codebook (preambles): 64 Zadoff-Chu sequences.
- Each preamble points to a *physical uplink shared channel* (PUSCH) opportunity (PO).
- RA users pick a preamble, transmit it in the RACH slot, and send their payload in the corresponding PO.
- The performance is dominated by preamble misdetection and preamble collisions.

Our Viewpoint on uRA



- A user may pick a random access codeword from a pre-defined codebook common to all users, and send it on the RACH slot.
- The receiver (base station) must detect the list of transmitted codewords (or "messages"), and estimate their corresponding channel vectors.
- The base station can immediately (super-low latency) reply with an ACK message allocating further UL/DL transmission resources.
- The uRA problem has been widely treated in the last few years for: a) Gaussian additive channels, b) multiantenna fading channels.
- For cell-free user-centric networks, uRA is "trickier".

Basic Model with Concentrated Antennas



- Activity Detection (AD): each UE has a unique access code. Goal: determine who is active.

- Unsourced RA (uRA): when active, UEs transmit a randomly chosen codeword of the same codebook. Goal: determine the set of active messages.

- Similar but some fundamental differences ...

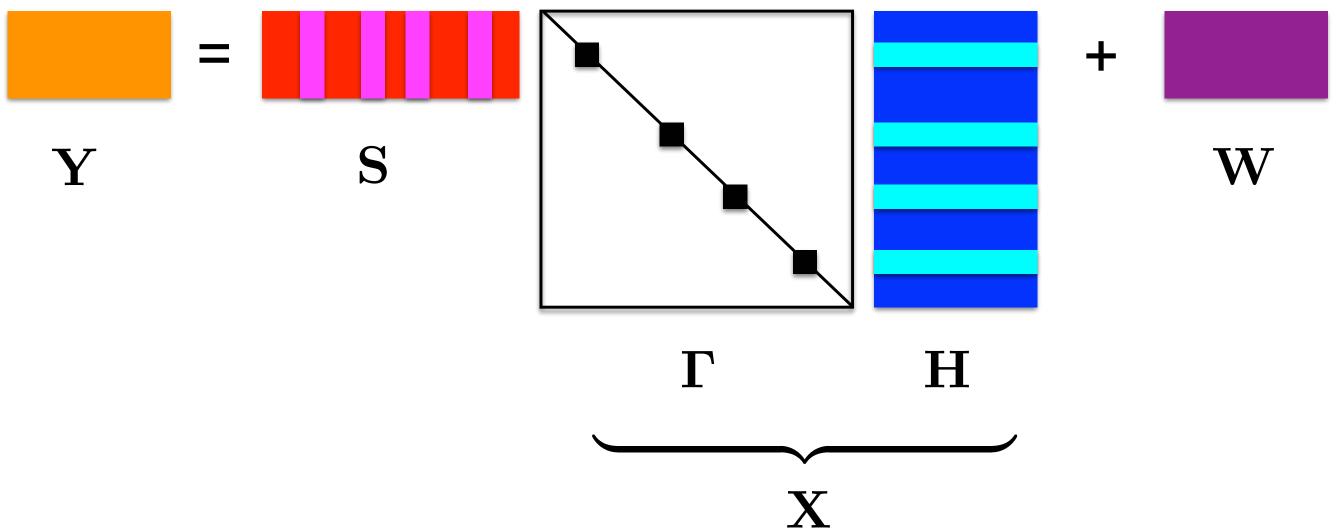
Model for Concentrated Antennas

- The received baseband signal over the L channel uses and the M antennas:

$$\mathbf{Y} = \mathbf{S}\mathbf{A}\mathbf{G}^{1/2}\mathbf{H} + \mathbf{W}$$

  where $\mathbf{W}$ is Gaussian i.i.d. noise.

- $\mathbf{\Gamma} = \mathbf{A}\mathbf{G} = \text{diag}(\gamma)$, where $\gamma_k = a_k g_k$ for user k with LSFC g_k.
- $\mathbf{X} = \mathbf{\Gamma}\mathbf{H}$ contains Bernoulli-Gaussian rows. Each k-th row has i.i.d. $\mathcal{CN}(0, g_k)$the elements, given $a_k = 1$.



Scaling Regimes for $K_{\text{tot}}, K_a, L, M$

- Compressed Sensing (CS) regime: in order to obtain a "stable" estimate the (sparse) rows of $\mathbf{\Gamma}^{1/2}\mathbf{H}$ we need $L \geq K_a \log(K_{\text{tot}}/K_a)$ (more measurements than unknowns).

- Identifiability regime (quadratic): two K_a-sparse vectors $\gamma, \gamma' \in \mathbb{R}_+^{K_{\text{tot}}}$ can be distinguished based on $\mathbf{Y}$ if $\mathbf{A}(\mathbf{\Gamma} - \mathbf{\Gamma}')\mathbf{A}^{\mathsf{H}} \neq \mathbf{0}$. This yields $K_a \leq L^2$ (quadratic in the signature dimension).

- Achievability of the quadratic regime: AMP fails (as well as any CS algorithm) but a relaxed ML algorithm, practically implemented by componentwise rank-1 update minimization, achieves the quadratic regimes [Fengler, Haghighatshoar, Jung, and GC, TIT 2021].

- Note: Beyond the linear CS regime, it is "impossible" to obtain "good" channel estimates (activity can be still detected for large M, but the estimated channels has large MSE). Therefore, the quadratic regime is intrinsically "non-coherent".

Key Difference Between AD and uRA

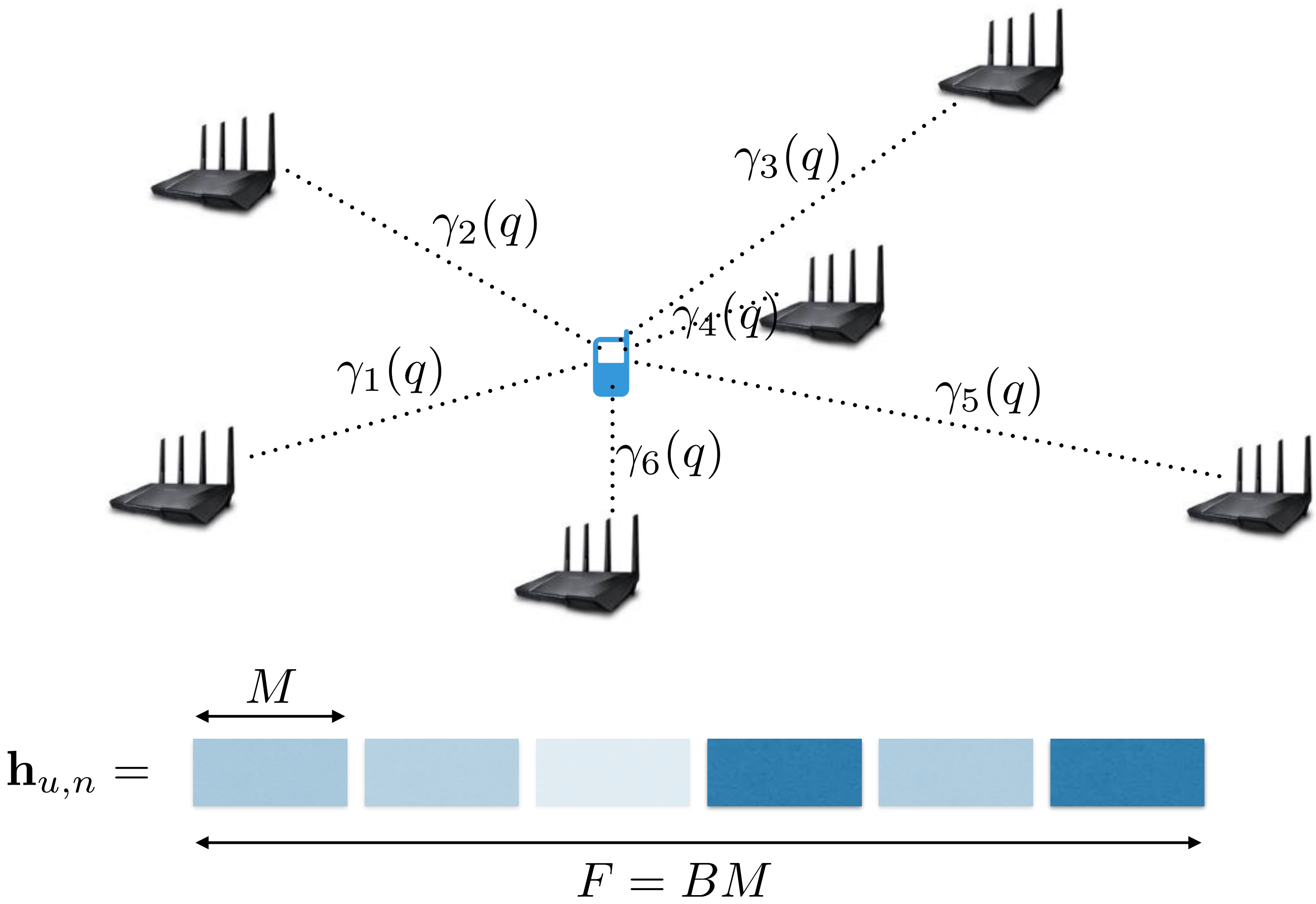
- In AD, provided that the users' LSFCs are known, we can treat $\mathbf{X} = \mathbf{\Gamma H}$ as row-wise Bernoulli-Gaussian: Bayesian estimation formulation is "relatively simple", in particular the Posterior Mean Estimate (PME) denoising function in AMP is tractable.

- In uRA, $K_{\rm tot}$ is irrelevant (it could be arbitrarily large): what counts is the number of codewords N (number of columns of $\mathbf{S}$).

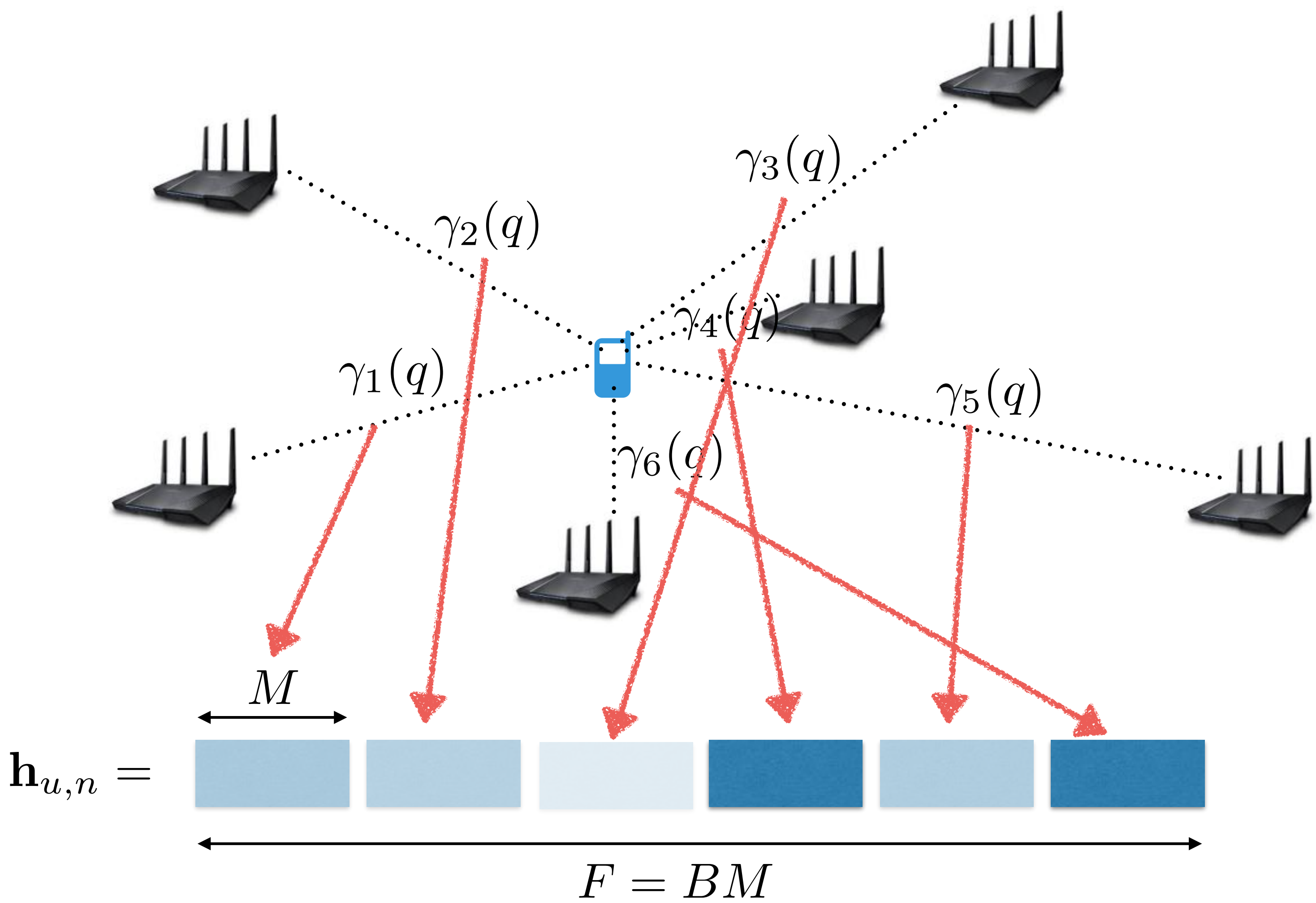
- Any active user can pick any codeword: a fixed correspondence between the columns of $\mathbf{S}$ and the LSFCs is not possible.

- As a consequence, $\mathbf{X} = \mathbf{\Gamma H}$ is not row-wise Bernoulli-Gaussian: Bayesian estimation formulation is "much more complicated" (and heavily relies on assumptions on the LSFC distribution for randomly placed users, .. risk of model mismatch, etc ...).

User-Location Dependent LSFC Profile



User-Location Dependent LSFC Profile

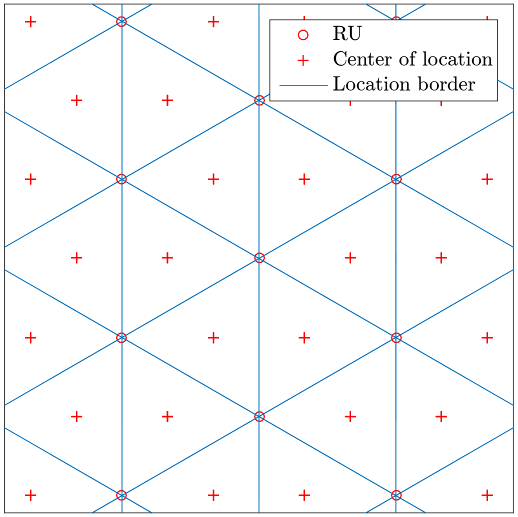


LSFC Profile Clustering

- The ensemble of all LSFC profiles

$$\boldsymbol{\gamma}(q) = (\gamma_1(q), \gamma_2(q), \ldots, \gamma_B(d)) \quad q \in \mathcal{D}$$

  forms a "source": we design a VQ for this source and each quantization region $\mathcal{D}_u$ (cluster) is associated to an uRA codebook $\mathbf{S}_u$, and to a cluster representative $\mathbf{g}_u = (g_{u,1}, g_{u,2}, \ldots, g_{u,B})$.
- In the case of standard pathloss radial function, the clusters correspond to Voronoi regions.



LSFC Profile Clustering

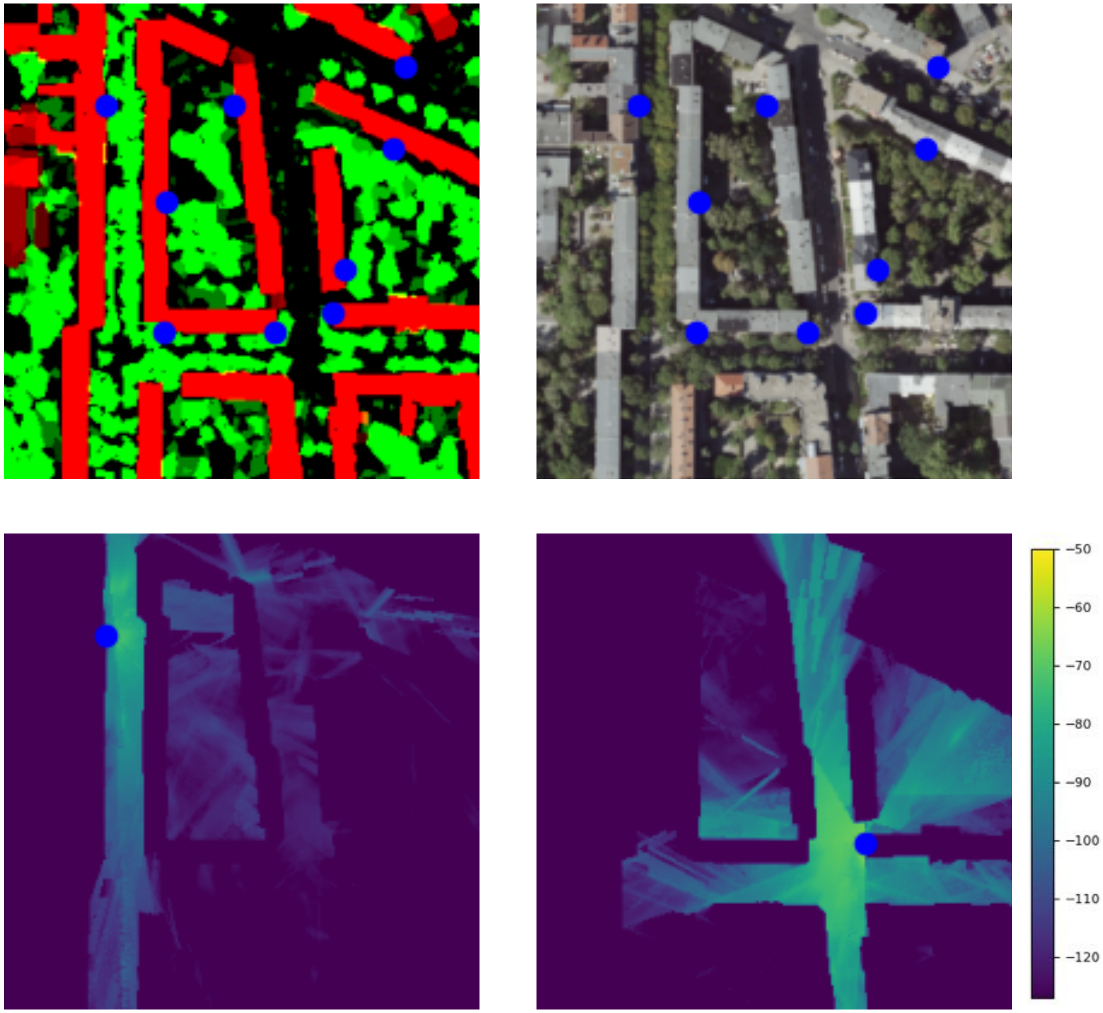


Fig. 1: City map with buildings in red, vegetation in green and RUs in blue, aerial image, two examples of LSFC maps in dB for specific RUs

LSFC Profile Clustering

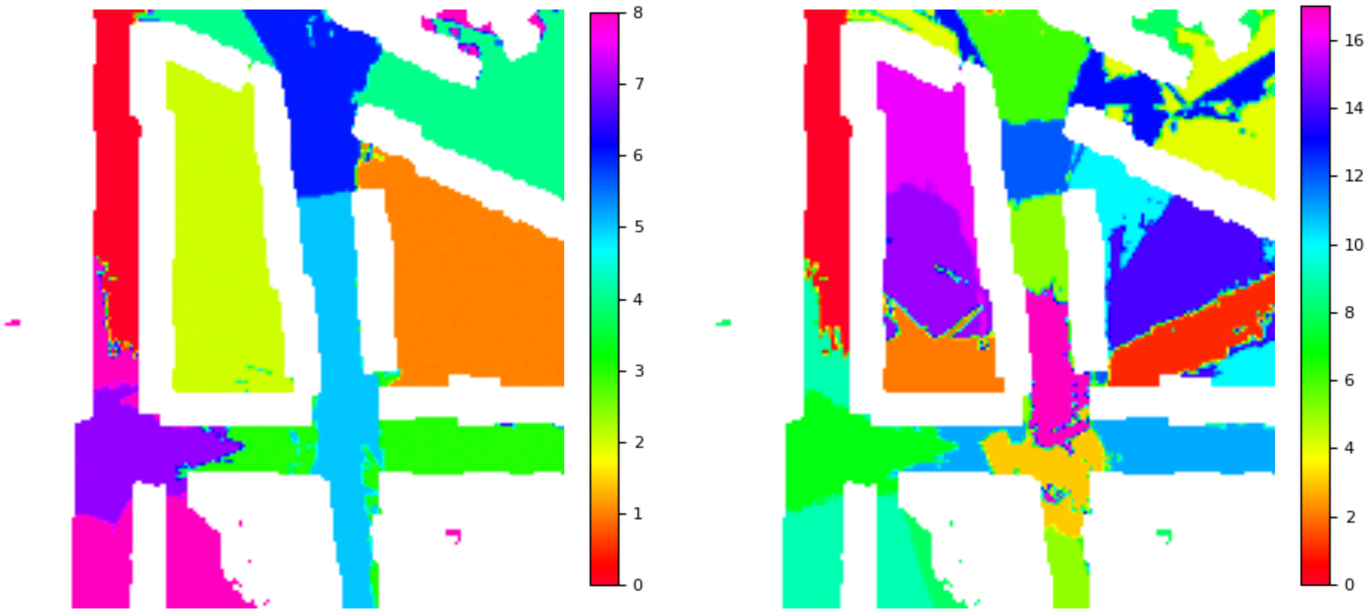
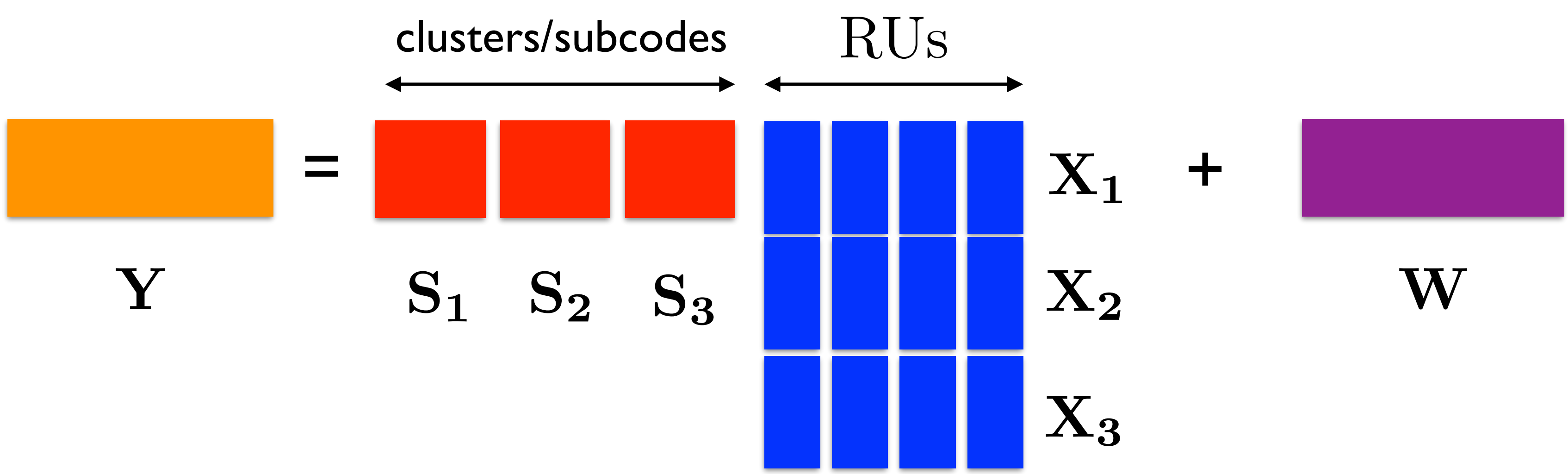


Fig. 2: Network topology with 9 and 18 clusters used in the numerical results of this paper.

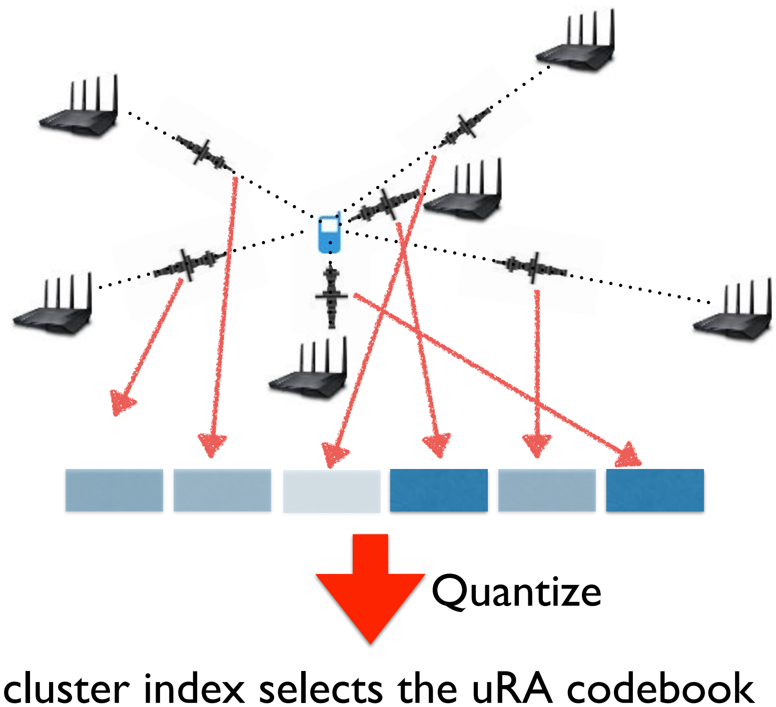
Our Idea: Location-based uRA code partitioning

- All users in "location" $u \in \mathcal{U}$ make use of codebook $\mathbf{S}_u$.
- The detector assumes users in the same cluster as co-located, having the same cluster representative LSFC profile $\mathbf{g}_u$.
- This establishes a fixed relation between codewords and LSFCs.
  - B. Cakmak, E. Gkiouzepi, M. Opper, and G. Caire. "Joint message detection and channel estimation for unsourced random access in cell-free user-centric wireless networks." IEEE Transactions on Information Theory (2025).

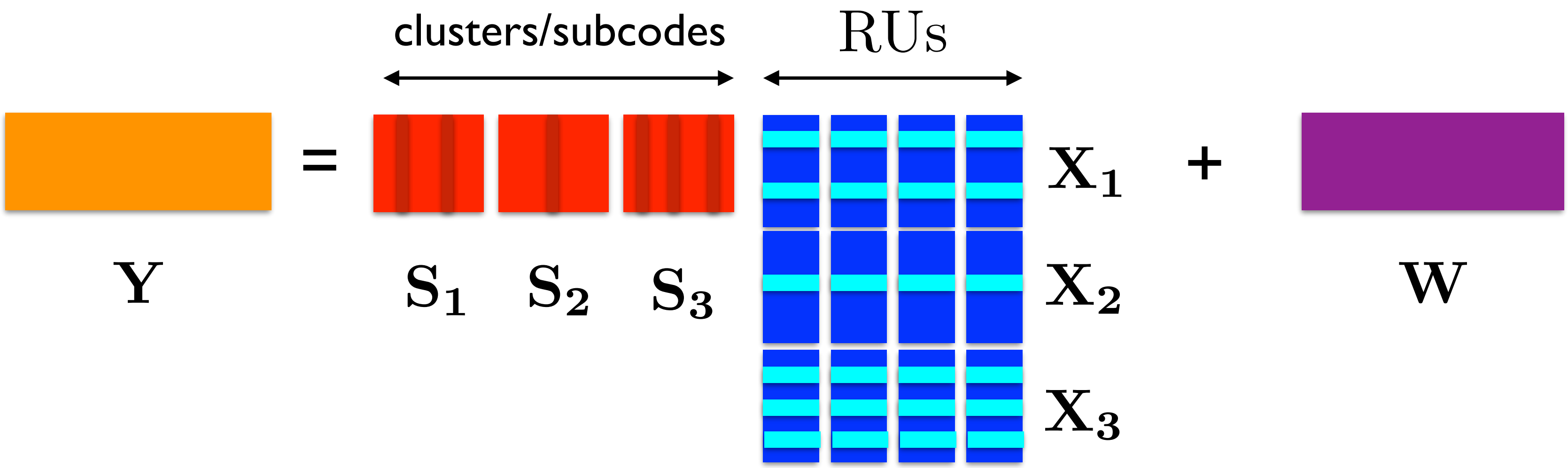


Trigger Frame and LSFC Cluster

- How can the “idle” UEs determine in which LSFC cluster they are?
- In the trigger frame announcing the RACH slot, all RUs send a unique signature sequence (with possible large spatial reuse factor). Each UE can measure the received power for each sequence and map the vector of RSSs into a region index , e.g., see:
  - Testi, Enrico, Andrea Giorgetti, and Giuseppe Caire. ”Weighted Centroid Localization in Cell-Free mMIMO: A Stochastic Geometry Perspective.” IEEE Transactions on Wireless Communications 25 (2026): 13042-13055.



Problem: find the "active codewords"



- Find the transmitted columns of the matrices $\{\mathbf{S}_u : u \in [U]\}$
- Find the non-zero rows of the matrices $\{\mathbf{X}_u : u \in [U]\}$
- The $N_u \times F$ matrices $\mathbf{X}_u$ have i.i.d rows and are "row sparse" due to the Bernoulli random activity (an average fraction $(1 - \lambda_u)$ of rows is identically zero).
- For the sake of analysis, we choose $\mathbf{S}_u \sim_{\text{i.i.d.}} \mathcal{CN}(\mathbf{0}, 1/L)$ of dimensions $L \times N_u$, and we assume $N_u/L = \alpha_u$ as $L \to \infty$ (system scaling parameter).

Multisource AMP (1)

For the system at hand, we consider the following AMP algorithm:

- Initialize: $\mathbf{X}_u^{(1)} = \mathbf{0}$ for $u \in [U]$ and $\mathbf{Z}^{(0)} = \mathbf{0}$.
- For iteration steps $t = 1, 2, \ldots, T$, repeat:

$$\mathbf{V}_u^{(t)} = \mathbf{S}_u \mathbf{X}_u^{(t)} - \alpha_u \mathbf{Z}^{(t-1)} \mathbf{Q}_u^{(t)} \tag{1a}$$

$$\mathbf{Z}^{(t)} = \mathbf{Y} - \sum_{u=1}^{U} \mathbf{V}_u^{(t)} \tag{1b}$$

$$\mathbf{R}_u^{(t)} = \mathbf{S}_u^{\mathsf{H}} \mathbf{Z}^{(t)} + \mathbf{X}_u^{(t)} \tag{1c}$$

$$\mathbf{X}_u^{(t+1)} = \eta_{u,t}(\mathbf{R}_u^{(t)}) \tag{1d}$$

Multisource AMP (2)

- where $\eta_{u,t}(\cdot) : \mathbb{C}^F \to \mathbb{C}^F$ is an appropriately defined deterministic and (u,t)-dependent "denoiser" function.

- $\eta_{u,t}(\cdot)$ applied to an $N_u \times F$ matrix $\mathbf{R}_u$ denotes the $N \times F$ matrix with its nth row given by $\eta_{u,t}(\mathbf{r}_n)$, i.e.,

$$\eta_{u,t}(\mathbf{R}) = [\eta_{u,t}(\mathbf{r}_1)^\top, \eta_{u,t}(\mathbf{r}_2)^\top, \cdots, \eta_{u,t}(\mathbf{r}_{N_u})^\top]^\top .$$

- where we define the expectation of the Jacobian matrix

$$\mathbf{Q}_u^{(t+1)} \doteq \mathbb{E}[\eta'_{u,t}(\mathbf{x}_u + \boldsymbol{\phi}^{(t)})],$$

with $\mathbf{Q}_u^{(1)} = \mathbf{0}$, $\mathbf{x}_u$ is a random vector distributed as the rows of $\mathbf{X}_u$, and $\{\boldsymbol{\phi}^{(t)}\}_{t\in[T]}$ is a Gaussian process (see later) independent of $\mathbf{x}_u$.

State Evolution

Definition 1. (State Evolution) *Let* $\{\boldsymbol{\phi}^{(t)} \in \mathbb{C}^{1\times F}\}_{t\in[T]}$ *be a zero-mean (discrete-time) Gaussian process with its two-time covariances* $\mathbf{C}^{(t,s)} \doteq \mathbb{E}[(\boldsymbol{\phi}^{(t)})^{\mathsf{H}}\boldsymbol{\phi}^{(s)}]$ *for all* $t, s \in [T]$ *constructed recursively according to*

$$\mathbf{C}^{(t,s)} = \sigma_w^2\mathbf{I} + \sum_{u=1}^{U} \alpha_u \mathbb{E}[(\mathbf{x}_u^{(t)} - \mathbf{x}_u)^{\mathsf{H}}(\mathbf{x}_u^{(s)} - \mathbf{x}_u)] \;, \tag{2}$$

where we define the random vectors for $t \in [T]$ *and* $u \in [U]$

$$\mathbf{x}_u^{(t+1)} := \eta_{u,t}(\mathbf{x}_u + \boldsymbol{\phi}^{(t)}), \tag{3}$$

independent of $\mathbf{x}_u^{(1)}$. ◊

Main Result

Theorem 1. *Under mild assumptions on the distribution of the rows of* $\mathbf{X}_u$*, with i.i.d. sub-Gaussian elements of* $\mathbf{S}$*, for large* L *with* $N_u/L = \alpha_u$ *and finite* U *and* F*, and differentiable and Lipschitz-continuous denoiser function* $\eta_{u,t}$*, we have*

$$\mathbf{R}_u^{(t)} \simeq \mathbf{X}_u + \mathbf{\Phi}_u^{(t)}$$

where $\mathbf{\Phi}_u^{(t)} \sim_{\text{i.i.d.}} \phi^{(t)}$ *with the Gaussian processes* $\phi^{(t)}$ *given by the SE and the elements in the set* $\{\mathbf{\Phi}_u^{(t)}, \mathbf{X}_u\}_{u \in [U]}$ *are all mutually independent.* □

- This result is proved for any large but finite L in:

B. Cakmak, E. Gkiouzepi, M. Opper, and GC. "Joint message detection and channel estimation for unsourced random access in cell-free user-centric wireless networks." *IEEE Trans. on IT*, (2025).

“Operational” corollaries

- Decoupling principle: any n-th row of $\mathbf{R}_u^{(t)}$ has the asymptotic (large L) statistics

$$\mathbf{r}_{u,n}^{(t)} \sim \mathbf{x}_{u,n} + \boldsymbol{\phi}_{u,n}^{(t)}$$

where $\phi_{u,n}^{(t)} \sim \mathcal{CN}(\mathbf{0}, \mathbf{C}^{(t,t)})$.

- Convergence of the empirical squared error:

$$\frac{1}{N_u}(\mathbf{X}_u - \mathbf{X}_u^{(t)})^{\mathsf{H}}(\mathbf{X}_u - \mathbf{X}_u^{(t)}) \overset{a.s.}{\to} \mathbb{E}\left[(\mathbf{x}_u - \mathbf{x}_u^{(t)})^{\mathsf{H}}(\mathbf{x}_u - \mathbf{x}_u^{(t)})\right].$$

MSE and PME Bayesian Denoiser

- The decoupling principle and the MSE suggest to choose $\eta_{u,t}(\cdot)$ in order to minimize $\mathbb{E}\left[(\mathbf{x}_u - \mathbf{x}_u^{(t)})^{\mathsf{H}}(\mathbf{x}_u - \mathbf{x}_u^{(t)})\right]$.
- This yields the Posterior Mean Estimator (PME) for $\mathbf{x}_u$ form the observation $\mathbf{r}_u^{(t)} = \mathbf{x}_u + \boldsymbol{\phi}^{(t)}$, i.e.,

$$\eta_{u,t}(\mathbf{r}) = \mathbb{E}[\mathbf{x}_u|\mathbf{r}_u^{(t)}]$$

- Interestingly, both $\eta_{u,t}(\mathbf{r})$ and its Jacobian matrix $\eta'_{u,t}(\mathbf{r})$ can be obtained in closed form.

Closed-Form Expressions

- Consider the conditional mean $\eta(\mathbf{r}) \triangleq \mathbb{E}[a\mathbf{h}|\mathbf{r}]$ with $a \sim \mathrm{Bern}(\lambda)$, and $\mathbf{r} = a\mathbf{h} + \boldsymbol{\phi}$ with $\mathbf{h}, \boldsymbol{\phi}$ and a independent.
- We have the general simple result:

$$\eta(\mathbf{r}) = \frac{\mathbb{E}[\mathbf{h}|\mathbf{r}, a = 1]}{1 + \Lambda_{\mathrm{map}}(\mathbf{r})}$$

where

$$\Lambda_{\mathrm{map}}(\mathbf{r}) = \left(\frac{1-\lambda}{\lambda}\right) \frac{p(\mathbf{r}|a = 0)}{p(\mathbf{r}|a = 1)}$$

and where

$$\Lambda_{\mathrm{map}}(\mathbf{r}) \underset{a=1}{\overset{a=0}{\gtrless}} 1$$

the maximum a posteriori probability (MAP) decision test of a.

Closed-Form Expressions

- In particular, for $\mathbf{h} \sim \mathcal{CN}(\mathbf{0}, \mathbf{\Sigma})$, and $\phi \sim \mathcal{CN}(\mathbf{0}, \mathbf{C})$, we have

$$\mathbb{E}[\mathbf{h}|\mathbf{r}, a = 1] = \mathbf{r}(\mathbf{\Sigma} + \mathbf{C})^{-1}\mathbf{\Sigma}$$

$$\Lambda_{\mathrm{map}}(\mathbf{r}) = \left(\frac{1-\lambda}{\lambda}\right) \frac{|\mathbf{\Sigma} + \mathbf{C}|}{|\mathbf{C}|} \mathrm{e}^{-\mathbf{r}(\mathbf{C}^{-1} - (\mathbf{\Sigma}+\mathbf{C})^{-1})\mathbf{r}^{\mathsf{H}}} .$$

- We can also obtain the Jacobian matrix in the appealing compact form

$$\eta'(\mathbf{r}) = \frac{(\mathbf{\Sigma} + \mathbf{C})^{-1}\mathbf{\Sigma}}{1 + \Lambda_{\mathrm{map}}(\mathbf{r})} + \Lambda_{\mathrm{map}}(\mathbf{r})\mathbf{C}^{-1}\eta(\mathbf{r})^{\mathsf{H}}\eta(\mathbf{r})$$

Message Detection (1)

- Consider the AMP output after T iterations.
- Let $\mathbf{C} := \mathbf{C}^{(T,T)}$ and $\mathbf{R}_u := \mathbf{R}_u^{(T)} \sim \mathbf{X}_u + \mathbf{\Phi}_u^{(T)}$. The decoupled channel model suggests a row-by-row Neyman-Pearson binary test for the detection (active/inactive) of message (u, n) with the two hypotheses:

$$\mathbf{r}_{n,u} \sim \begin{cases} \mathcal{CN}(\mathbf{0}, \mathbf{C}) & a_{n,u} = 0 \text{ (Hypothesis } \mathcal{H}_0\text{)} \\ \mathcal{CN}(\mathbf{0}, \mathbf{\Sigma}_u + \mathbf{C}) & a_{n,u} = 1 \text{ (Hypothesis } \mathcal{H}_1\text{)} \end{cases}$$

- Although we use the prior activity probability λ for the PME denoiser, we prefer to use a Neyman-Pearson test for message activity detection since MD and FA probabilities have a different impact on the system performance.

Message Detection (2)

- The LLR threshold test yields a decision metric in the form of a Hermitian Quadratic form of Gaussian Circularly Symmetric Random Variables (HQF-GRV) under both $\mathcal{H}_0$ and $\mathcal{H}_1$.

- As a consequence, the MD and FA probabilities can be computed in closed form!!! (or approximated with any desired degree of accuracy using the method of Laplace Inversion with Gauss-Chebyshev Quadrature Rules.

• Ventura-Traveset, Javier, Giuseppe Caire, Ezio Biglieri, and Giorgio Taricco. ”Impact of diversity reception on fading channels with coded modulation. I. Coherent detection.” IEEE Transactions on Communications 45, no. 5 (2002): 563-572.

Achievable rate in the ACK/DL transmission

- Based on the active message channel estimates, for each UE (detected active message) we allocate a user-centric cluster corresponding by the Q RUs $b \in [B]$ with largest $\widetilde{g}_{u,b}$.
- We use MRT to transmit a beamformed coded ACK to the users (and possibly allocate resource for further data communication).
- Using the asymptotic analysis, we obtain the semi-closed form ergodic rate expression:

$$R_{u,n}^{\mathrm{UatF}} = \log\left(1 + \frac{\left|\sum_{b\in\mathcal{C}_u} \mathcal{M}_{u,b}\right|^2}{\sigma_w^2/\rho_{\mathrm{DL}} + \sum_{b\in\mathcal{C}_u} \mathcal{V}_{u,b} + L\sum_{u'\in[U]}\sum_{b\in\mathcal{C}_{u'}} \lambda_{u'}\alpha_{u'}\widetilde{g}_{u,b}\mathcal{Z}_{u',b}}\right),$$

where, for all $(u,b) \in [U]\times[B]$, we define

$$\mathcal{M}_{u,b} \triangleq \mathbb{E}\left[\mathbf{h}_{u,b}\,\eta_{u,T}(\mathbf{h}_{u,b} + \mathbf{z}_b\mathbf{C}_b^{\frac{1}{2}})^{\mathsf{H}}|\mathbf{h}_u, \mathbf{z} \in \mathcal{E}_u\right]$$

$$\mathcal{V}_{u,b} \triangleq \mathrm{Var}\left(\mathbf{h}_{u,b}\,\eta_{u,T}(\mathbf{h}_{u,b} + \mathbf{z}_b\mathbf{C}_b^{\frac{1}{2}})^{\mathsf{H}}|\mathbf{h}_u, \mathbf{z} \in \mathcal{E}_u\right),$$

and the Tx power normalization coefficient

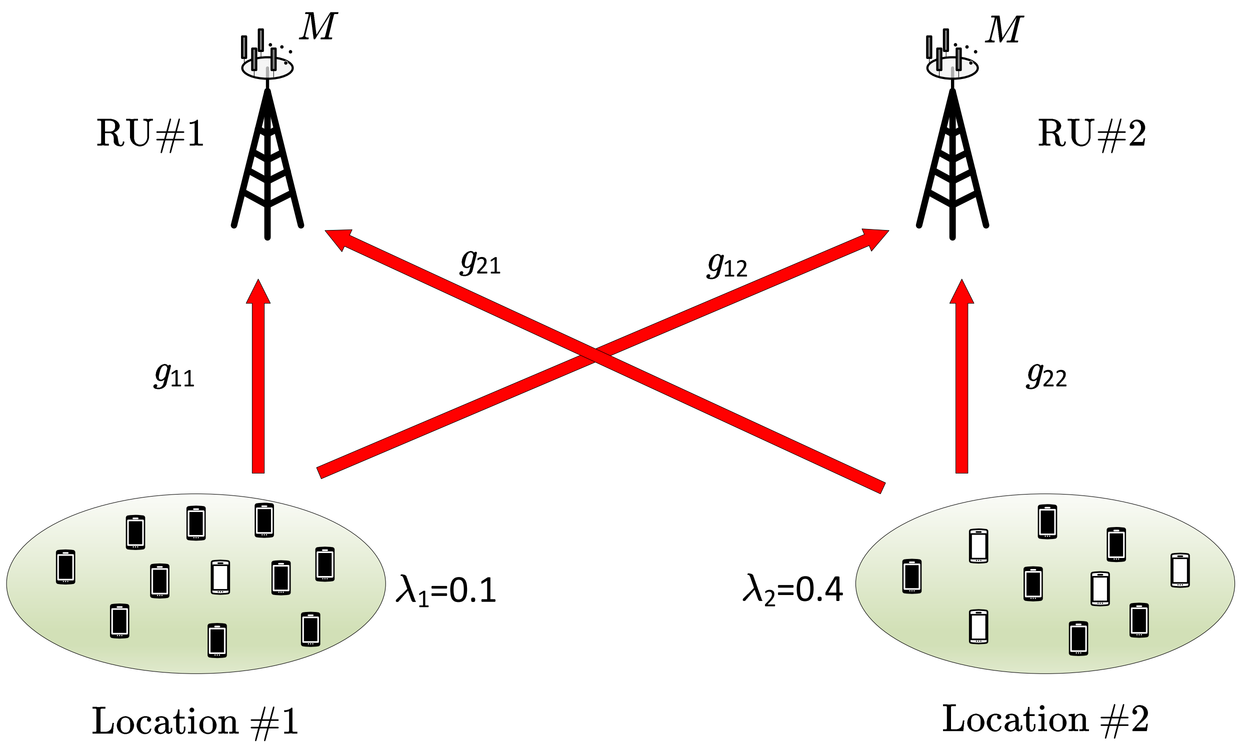
$$\rho_{\rm DL} = \frac{1}{L} \frac{\sum_{u=1}^{U} \lambda_u \alpha_u}{\sum_{b=1}^{B} \sum_{u \in \mathcal{S}_b} \lambda_u \alpha_u \mathcal{Z}_{u,b}}$$

with

$$\begin{aligned} \mathcal{Z}_{u,b} \quad &\triangleq \quad (1 - {\rm P}_u^{\rm md}) \mathbb{E}\left[\|\eta_{u,T}(\mathbf{h}_{u,b} + \mathbf{z}_b \mathbf{C}_b^{\frac{1}{2}})\|^2 \mid \mathbf{z}, \mathbf{h}_u \in \mathcal{E}_u \right] \\ &+ (\lambda_u^{-1} - 1) {\rm P}_u^{\rm fa} \mathbb{E}\left[\|\eta_{u,T}(\mathbf{z}_b \mathbf{C}_b^{\frac{1}{2}})\|^2 \mid \mathbf{z} \in \mathcal{F}_u \right]. \end{aligned}$$

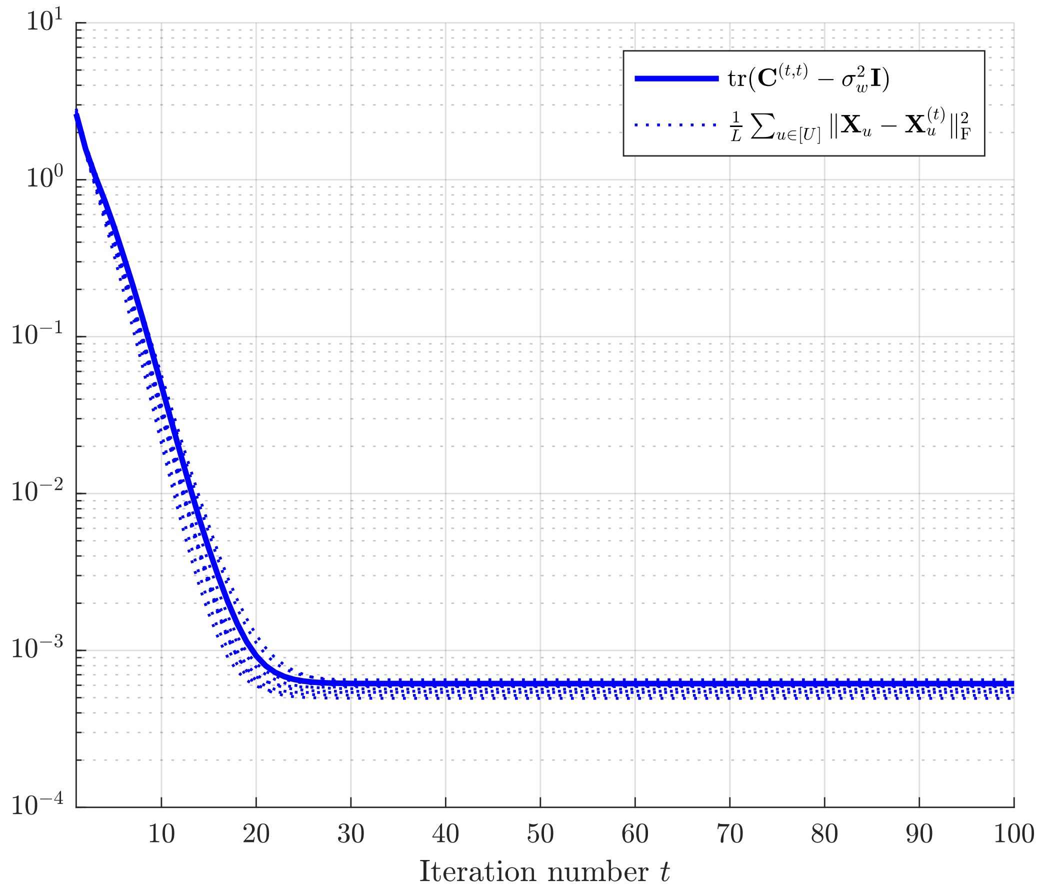
where $\mathbf{h}_u \sim \mathcal{CN}(\mathbf{0}, \mathbf{\Sigma}_u)$, $\mathbf{z} \sim_{\rm i.i.d.} \mathcal{CN}(0,1)$ are mutually independent, $\mathbf{h}_{u,b}$ and $\mathbf{z}_b$ denote the b-th segment of size $1 \times M$ of $\mathbf{u}_u$ and $\mathbf{z}$, respectively, and the events $\mathcal{E}_u$ and $\mathcal{F}_u$ are correct detection and false alarm events.

"Wyner model" with $U = B = 2$



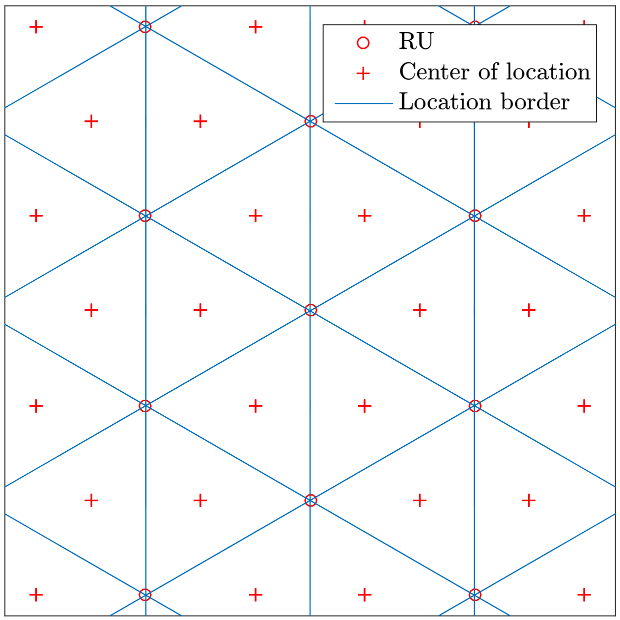
Toy Setup with $U = B = 2$

- $N_1 = N_2 = 2048$, $L = 1024$, SNR$= 10$ dB, $\lambda_1 = 0.1, \lambda_2 = 0.2$, $M = 2$.



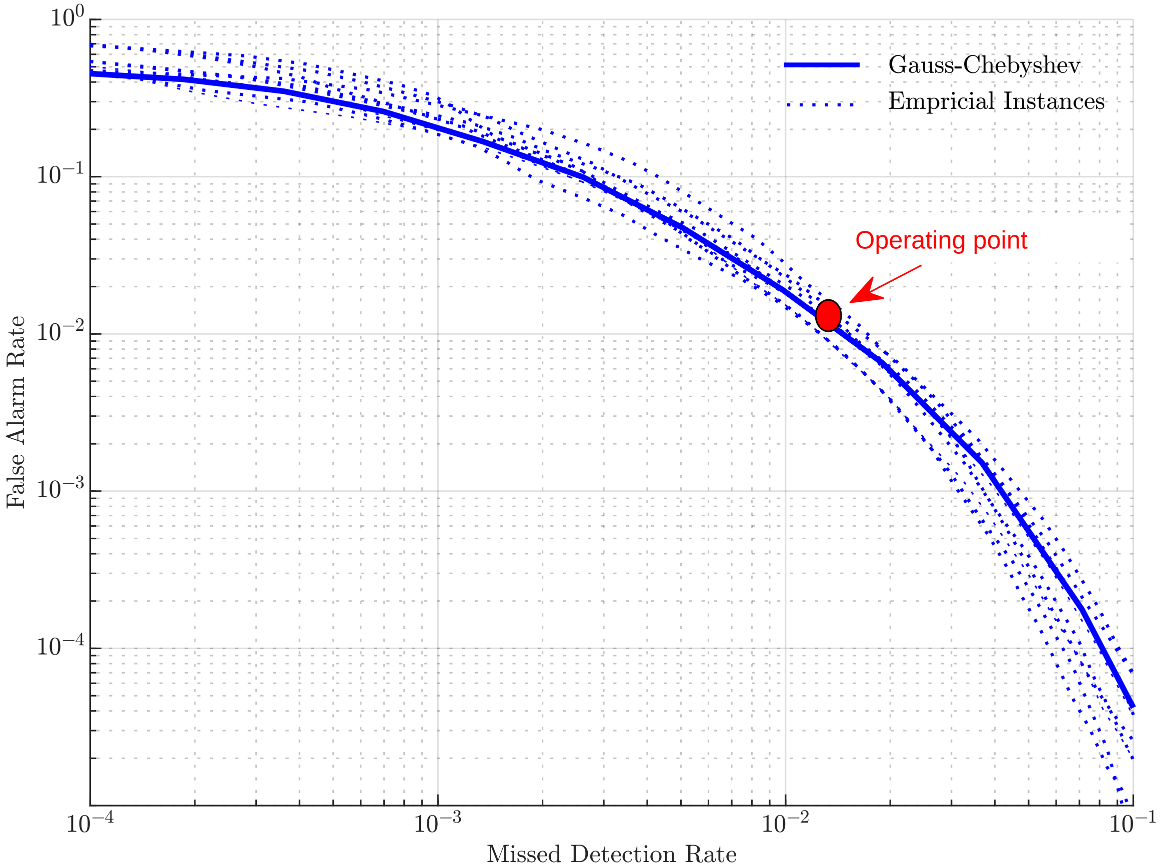
More Realistic Setup $U = 16$, $B = 12$

- $N_u = 2048$, $L = 1024$, realistic SNR and distance dependent pathloss model, $\lambda_u \in \{0.01, 0.03\}$, repeated in a periodic pattern.



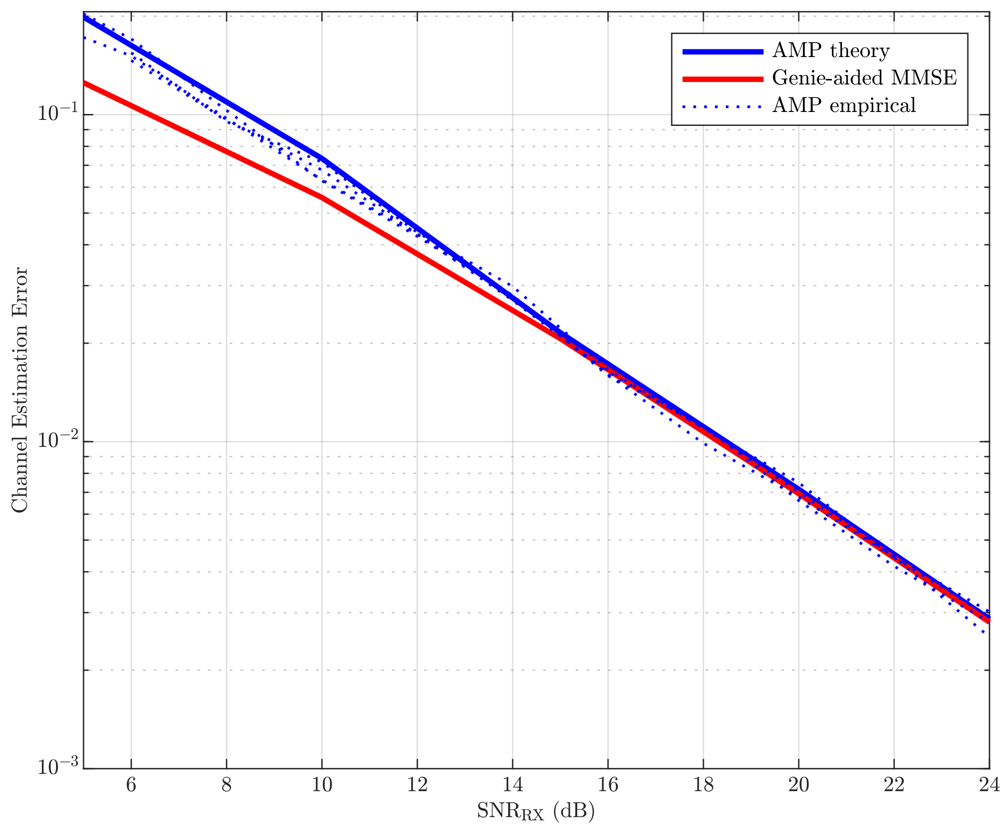
More Realistic Setup $U = 16$, $B = 12$

- We choose to work at the point where $P_{\mathrm{fa}} = P_{\mathrm{md}}$.



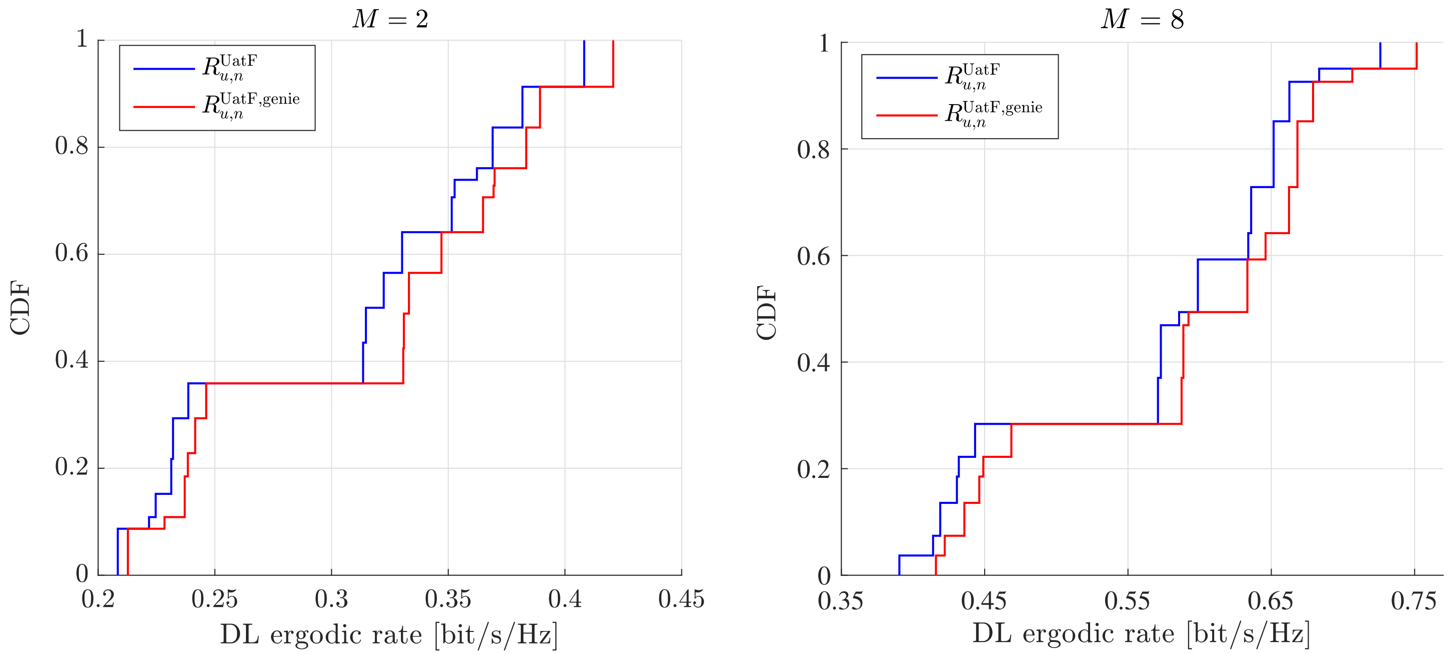
More Realistic Setup $U = 16$, $B = 12$

- In these conditions, the channel estimation for the messages in $\mathcal{A}_{\rm d}$ is excellent:



More Realistic Setup $U = 16$, $B = 12$

- Ergodic rate CDF (over the user population) for the MRT downlink transmission.



Non-Colocated Users and RSS-based positioning

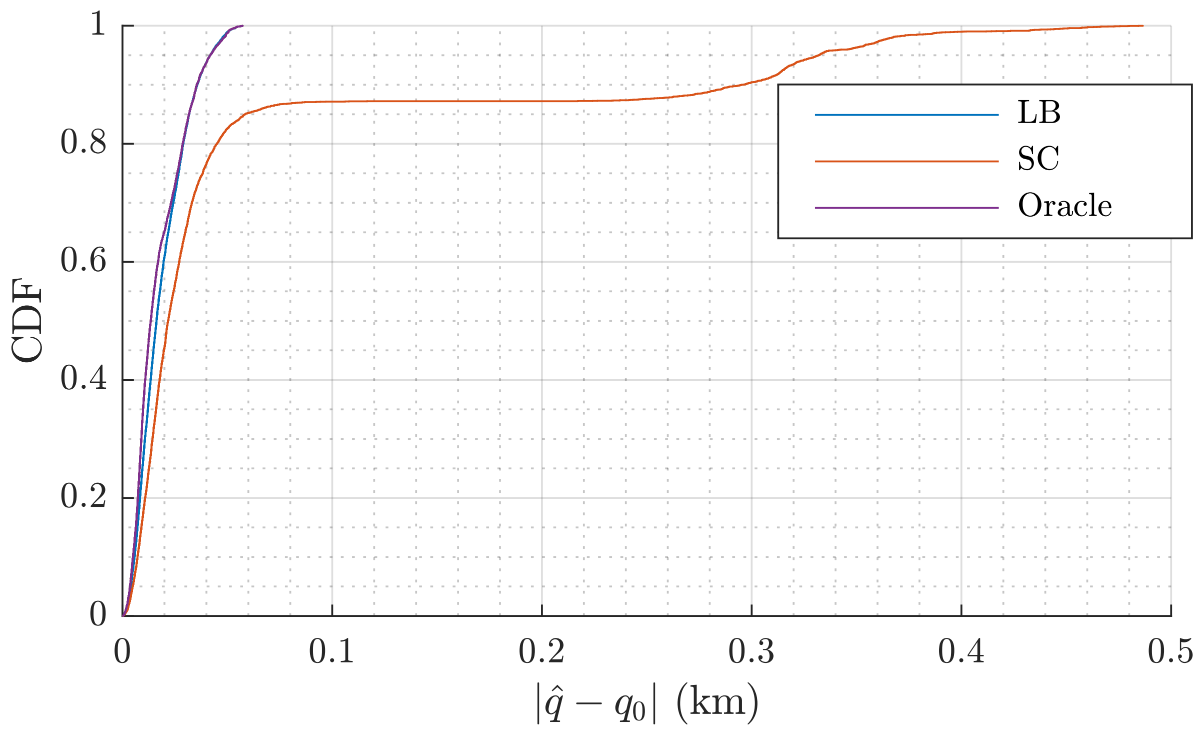
- For each message in $\widehat{\mathcal{A}}_u$, the system assumes that it is transmitted by some user in position $q \in \mathcal{D}_u$.
- In this case, the conditional statistics are Bernoulli-Gaussian Mixture and denoising function and message decision metric are more complicated (no simple closed-forms).
- Consider a discrete grid $\mathcal{Q}_u \subset \mathcal{D}_u$ and, under the condition that message (u, n) is active, we use the conditional distribution of $\mathbf{r}_{u,n} \sim g(\mathbf{r}; \mathbf{0}, \mathbf{\Sigma}(q) + \mathbf{C})$.
- This yields the MAP position estimator

$$\widehat{q} = \arg\min_{q \in \mathcal{Q}_u} \left\{ \log \left(\pi^N |\mathbf{\Sigma}(q) + \mathbf{C}| \right) + \log P_u(q) + \mathbf{r}^{\mathsf{H}} (\mathbf{\Sigma}(q) + \mathbf{C})^{-1} \mathbf{r} \right\}.$$

- To quantify the performance of this position estimator, we compare with an “oracle” that, for all active user in some (unquantized) positions $q_0 \sim f_u(\cdot)$, finds the point on the grid $\mathcal{Q}_u$ at minimum distance, i.e., finds $q^\star = \arg\min_{q \in \mathcal{Q}_u} |q - q_0|$.

Localization of random access users

- Case of radial pathloss function (triangular clusters of side 0.1 km).
- The localization performance is dominated by the grid quantization.



Localization of random access users

- Case of realistic (ray-tracing) pathloss function.

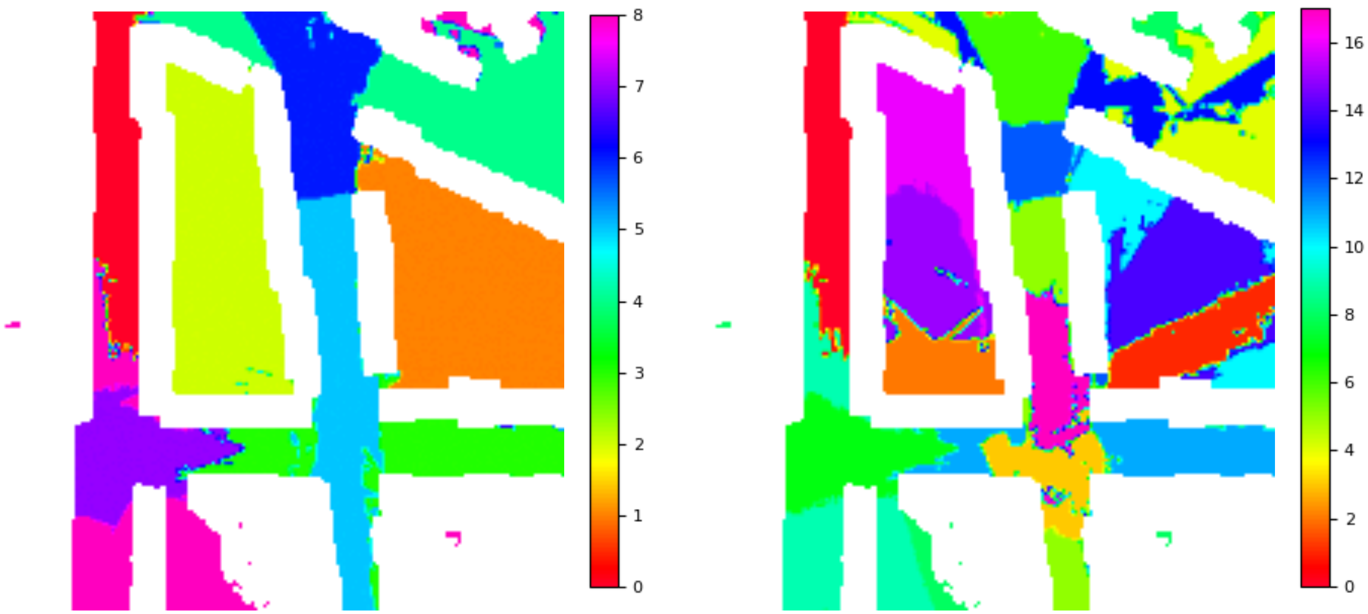
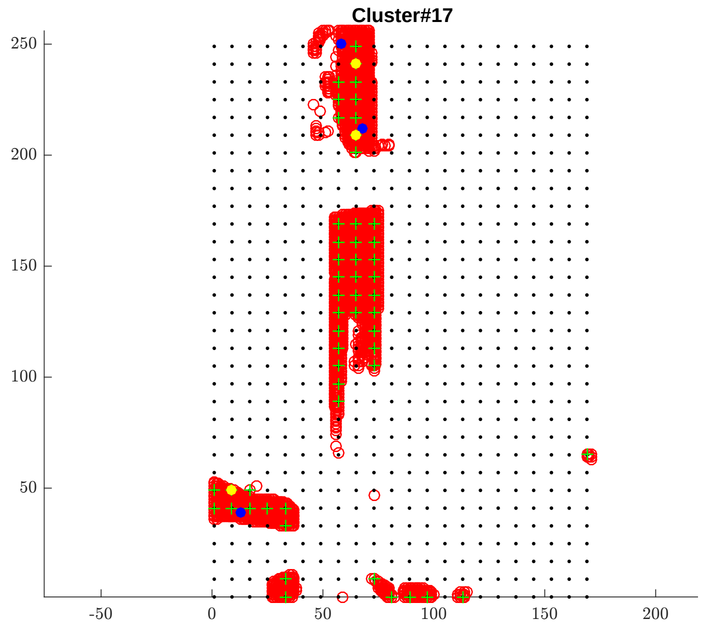
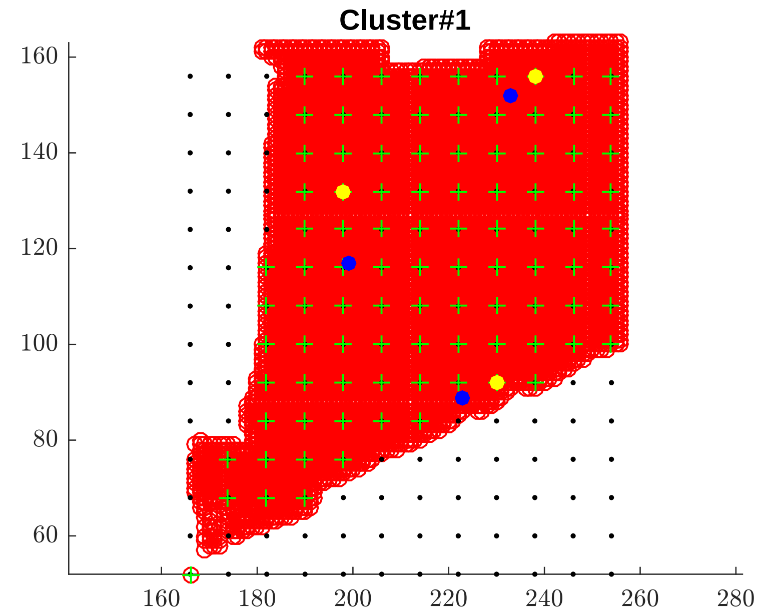


Fig. 2: Network topology with 9 and 18 clusters used in the numerical results of this paper.

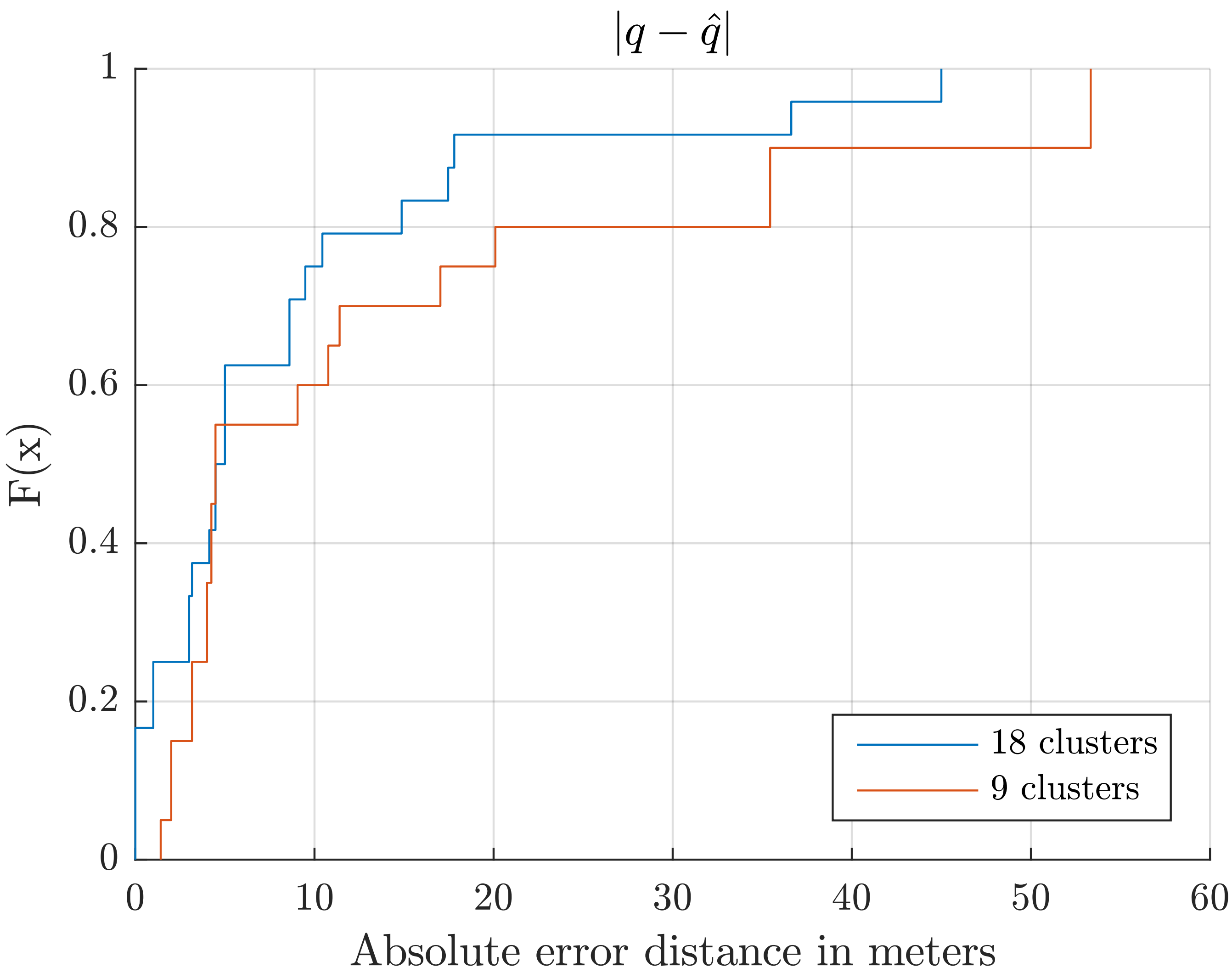
Localization of random access users

- Case of realistic (ray-tracing) pathloss function.



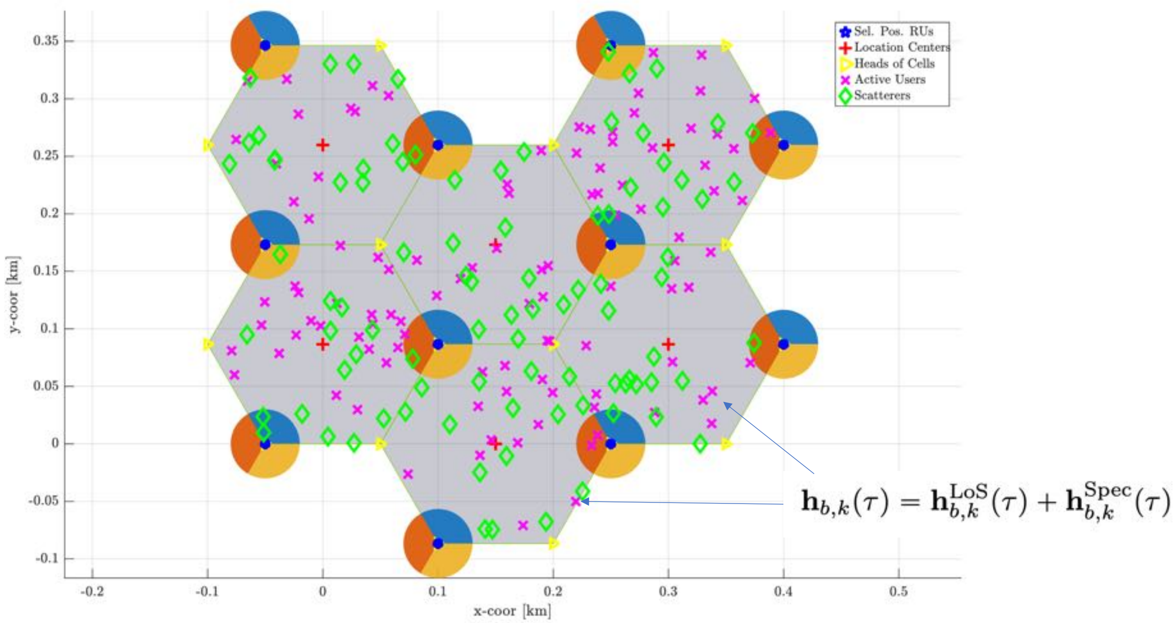


Localization of random access users



Extensions to Multipath/Rician Channels

- Work in progress with Simon Tarboush (previously presented at ELLIT last week).
- To relate AoA and TDoA of the LoS components to the UE positions, we need geometric consistency across the whole network.



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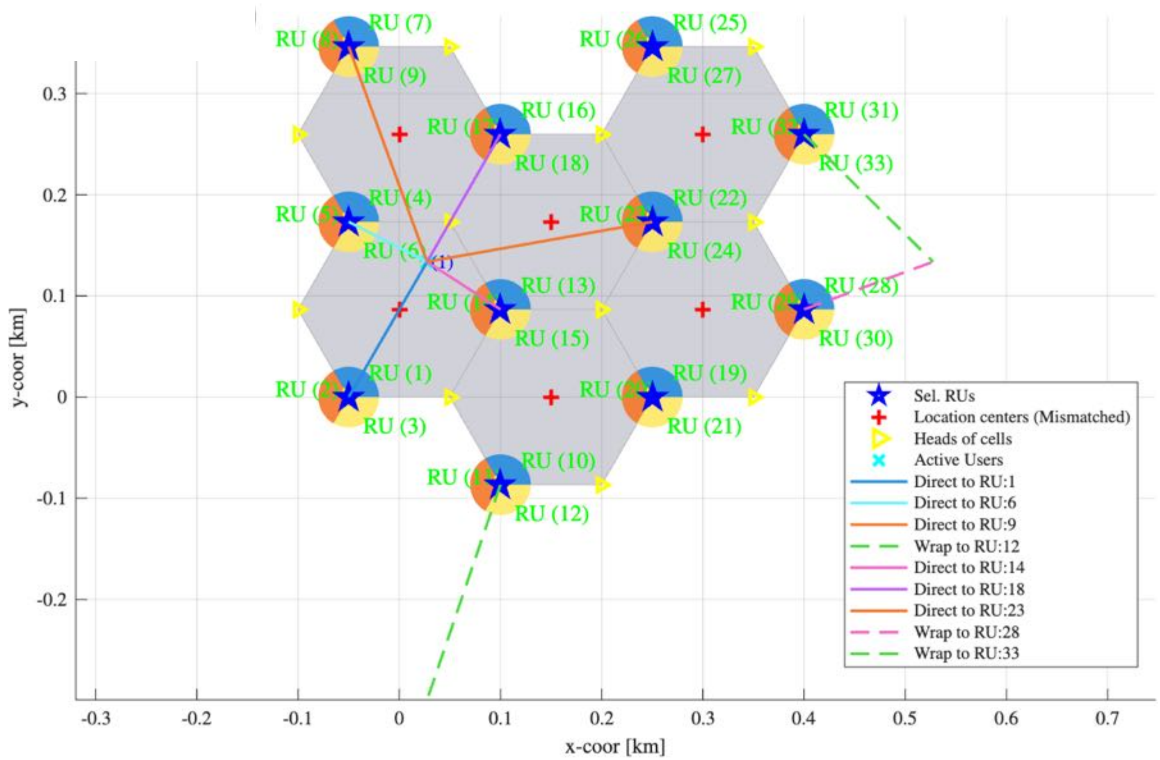
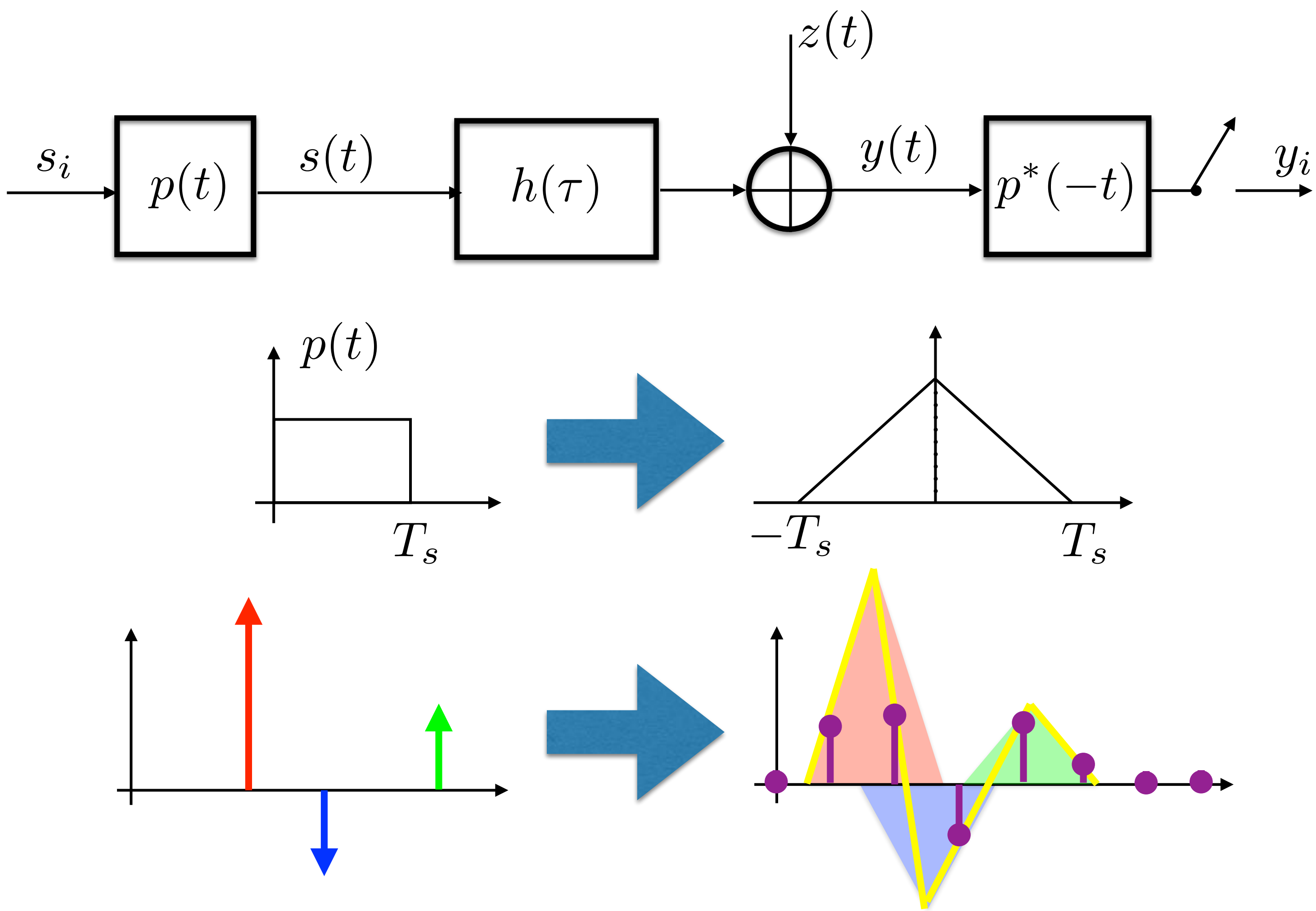


Continuous to Discrete Time Conversion

- The channel vectors become vectors of discrete-time impulse responses.

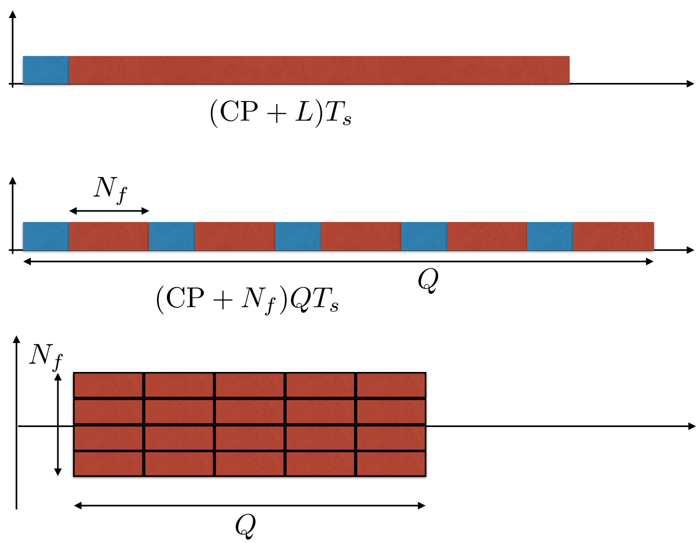


uRA Codewords Structure

- We consider a time-domain ZC-based "legacy" scheme, and a multicarrier extension of the proposed AMP-based scheme.

$$(\mathrm{CP}+L)T_s \approx (\mathrm{CP}+N_f)QT_s \quad \Rightarrow \quad Q \approx \frac{1}{2}\left(1+\frac{L}{\mathrm{CP}}\right)$$

by letting $N_f = \mathrm{CP} \geq \lceil \Delta\tau_{\max}/T_s \rceil$.



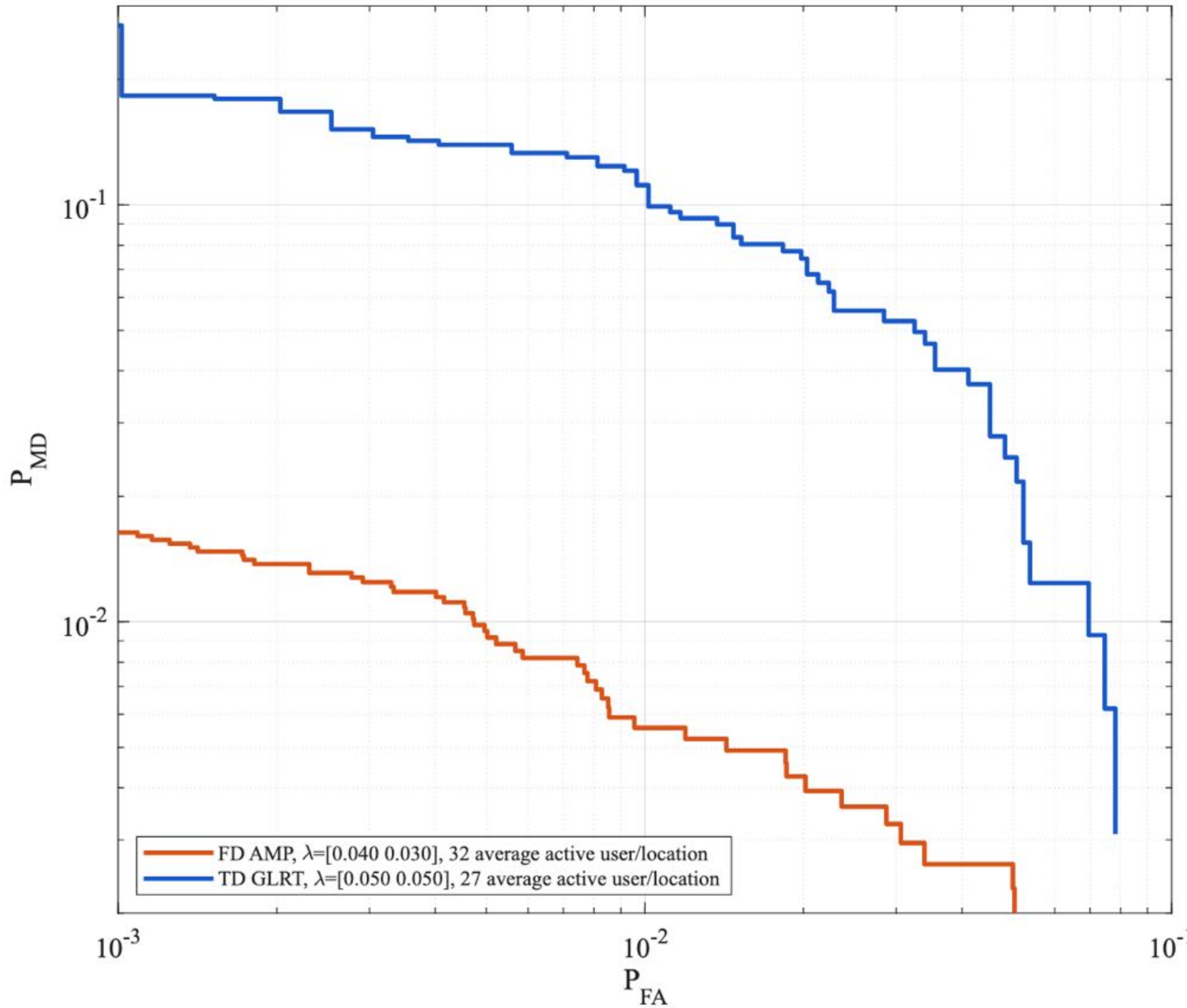
Challenges and On-Going Work

- Channel statistics are much more complicated (LoS contains delay and AoA, Rician with random phase, scattering components have antenna correlation and strength that depends on scatterers positions).

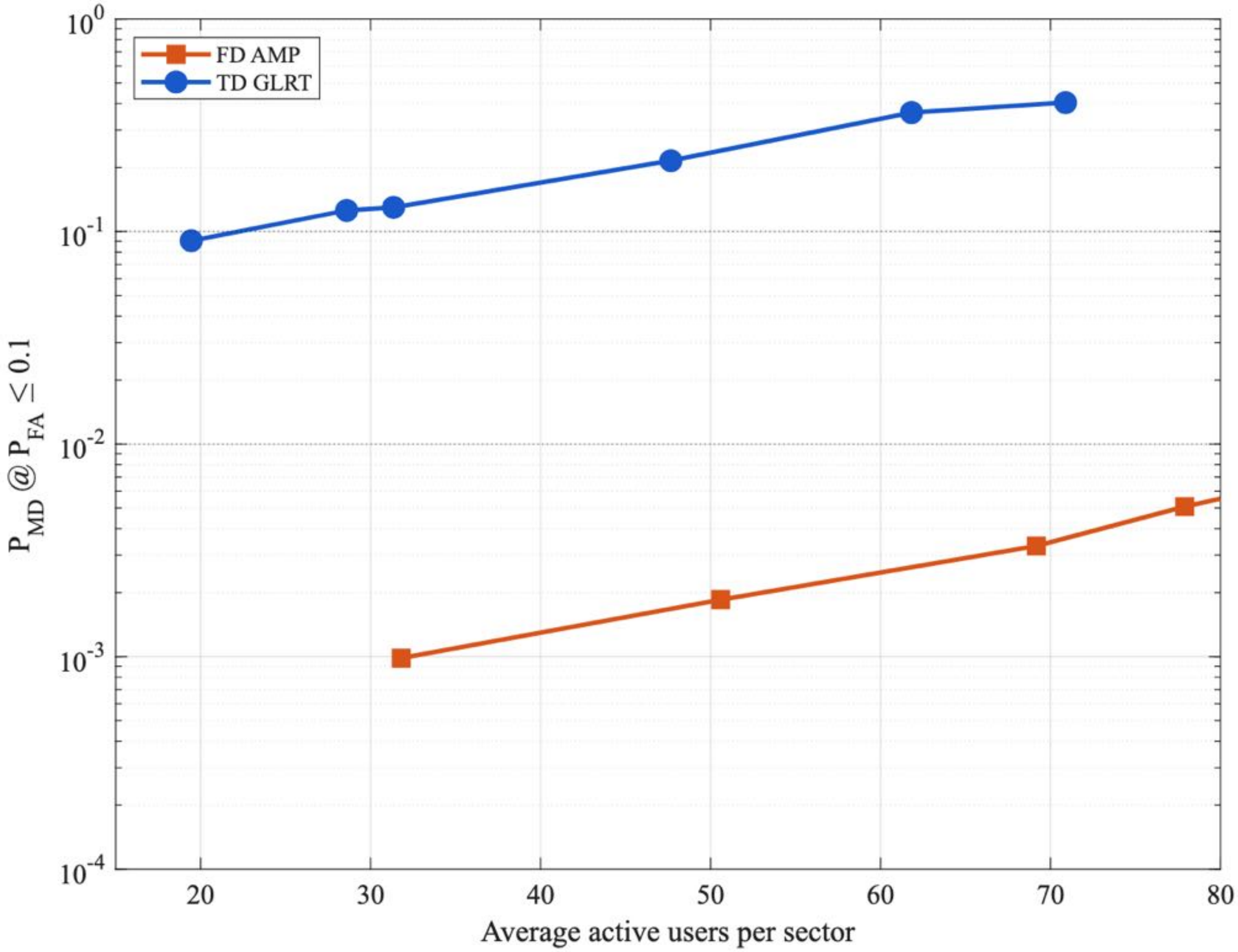
- Given what it is plausible to assume known (random access users joining the system sporadically with large idle times), design a suitable non-linear denoiser $\eta(\cdot)$ for AMP.

- Given the conditional AMP output statistics given the position of the “true active” users, design an approximated MAP position estimation.

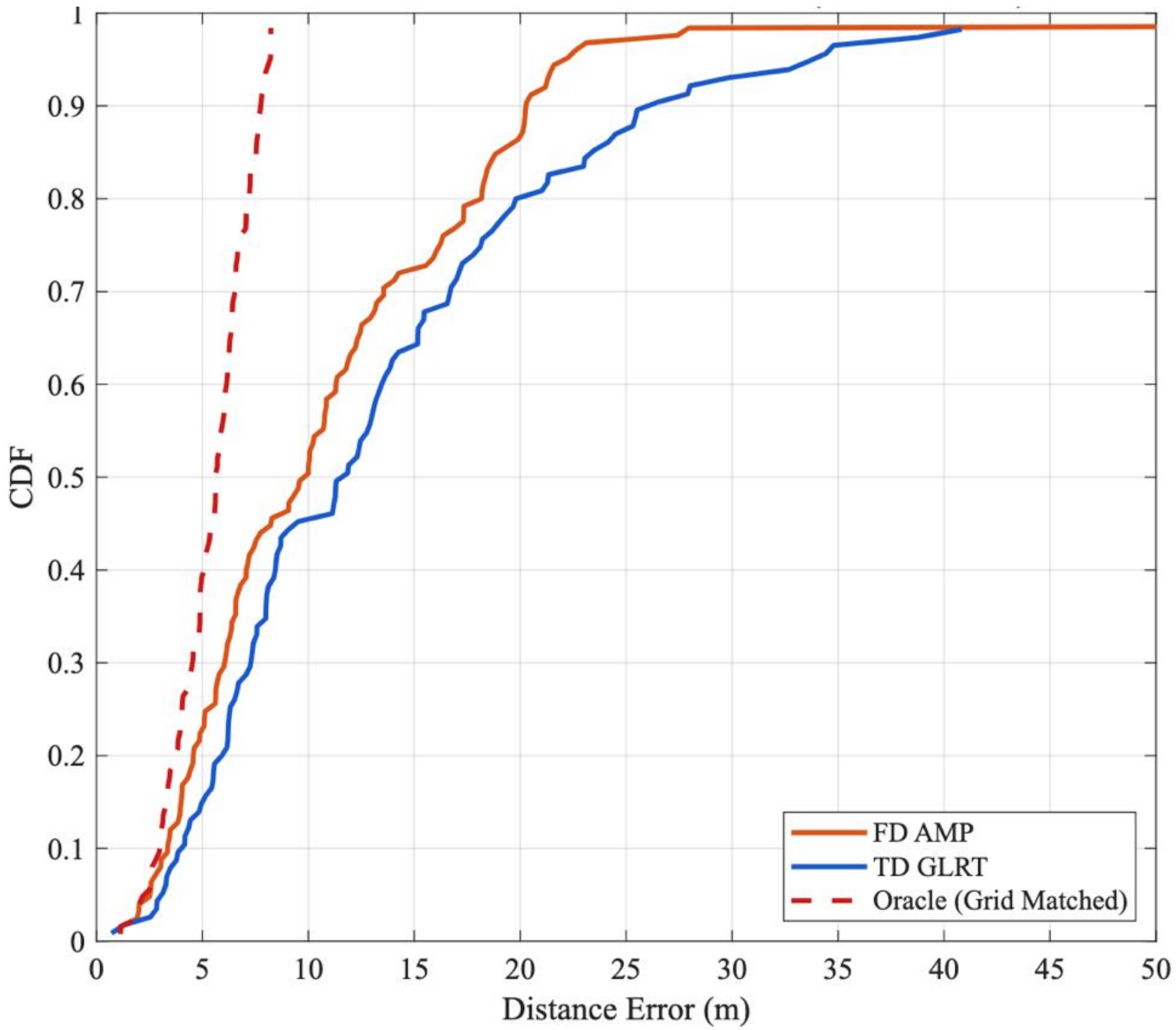
Some initial results



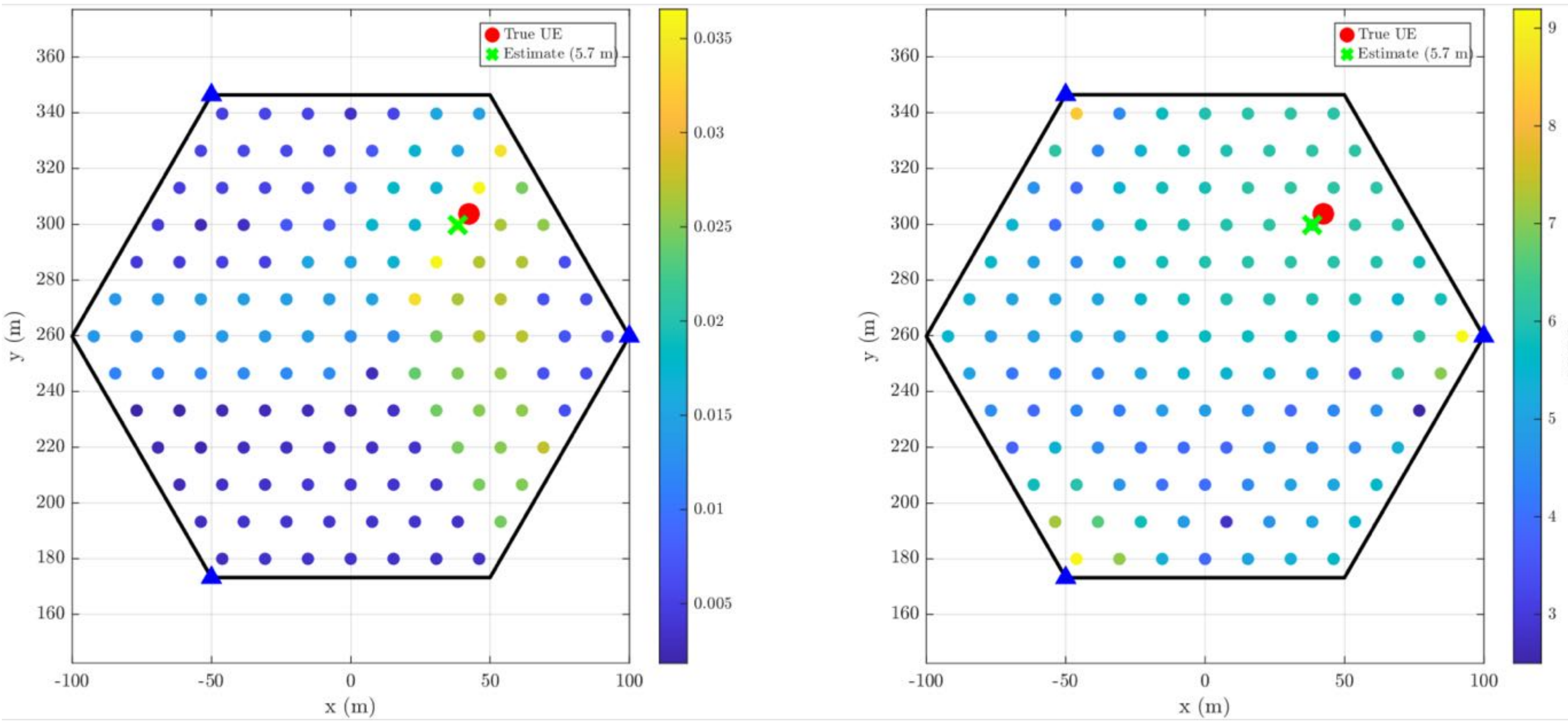
Some initial results



Some initial results



Some initial results



Conclusion

- Key Ideas:
  - spatial clustering (LSFC profiles or more in general "channel features map") and associate access codebooks to clusters;
  - a novel "multisource" AMP.
- The "decoupled" AMP output yields message detection, channel estimation, and active user positioning.
- The AMP asymptotic output statistics allows (almost) closed-form evaluation of large systems.
- The cluster formation can be done "instantaneously". No explicit association and pilot allocation (FULL SUPPORT FOR SEAMLESS CONNECTIVITY).

Thank You