GRACE-SERENA-Car2TERA Winter School

# Mm-wave Communication and Radar Sensing: Basic Principles and Research Trends

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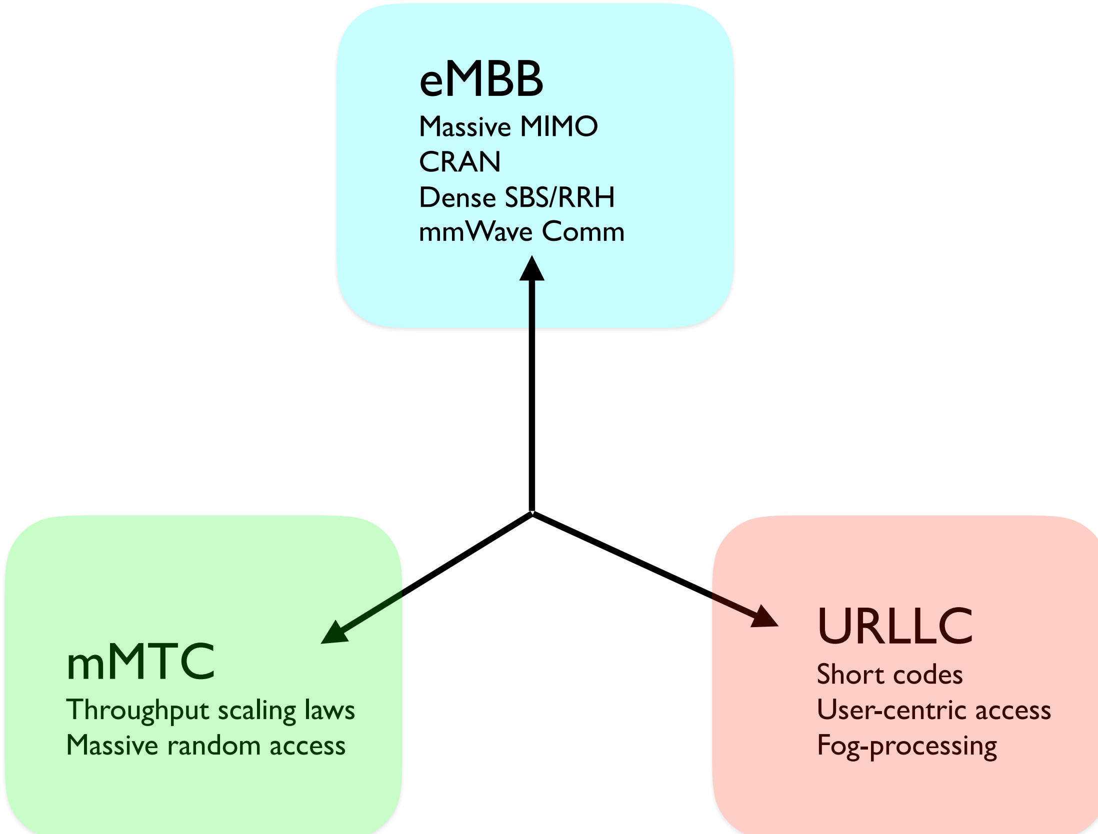
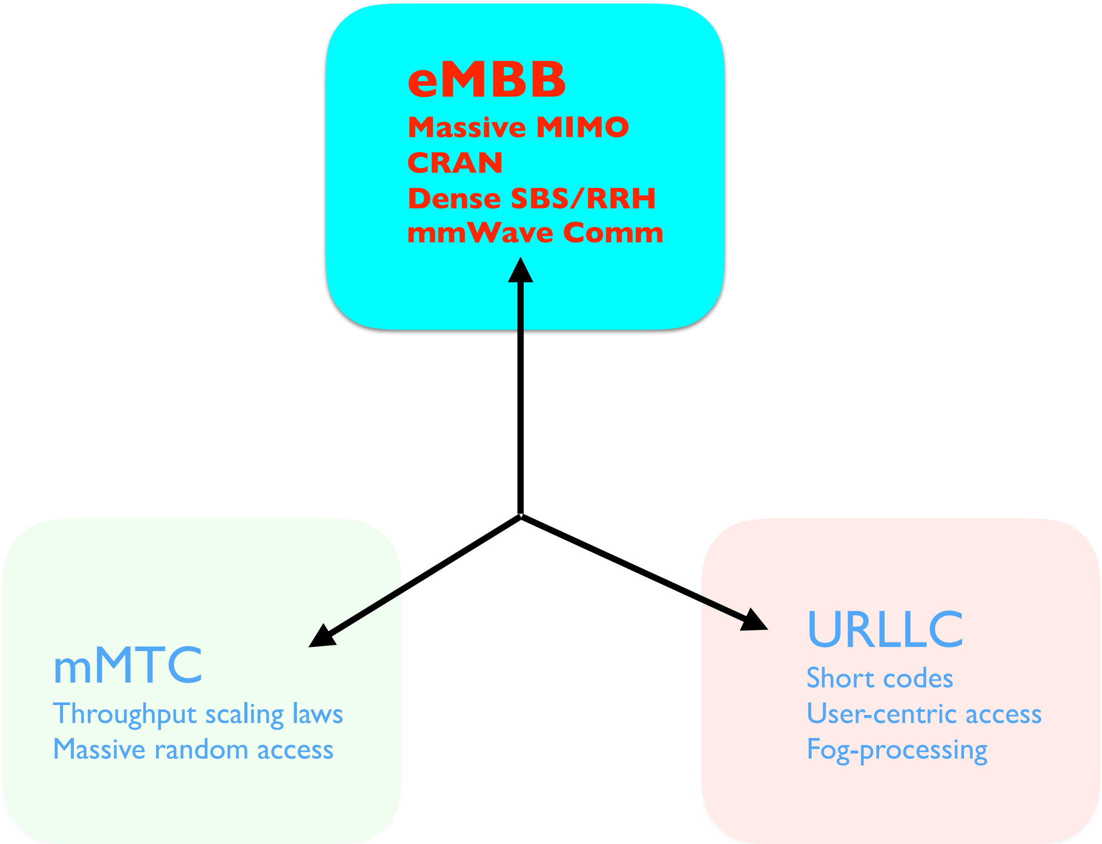
# The Three Axes of 5G



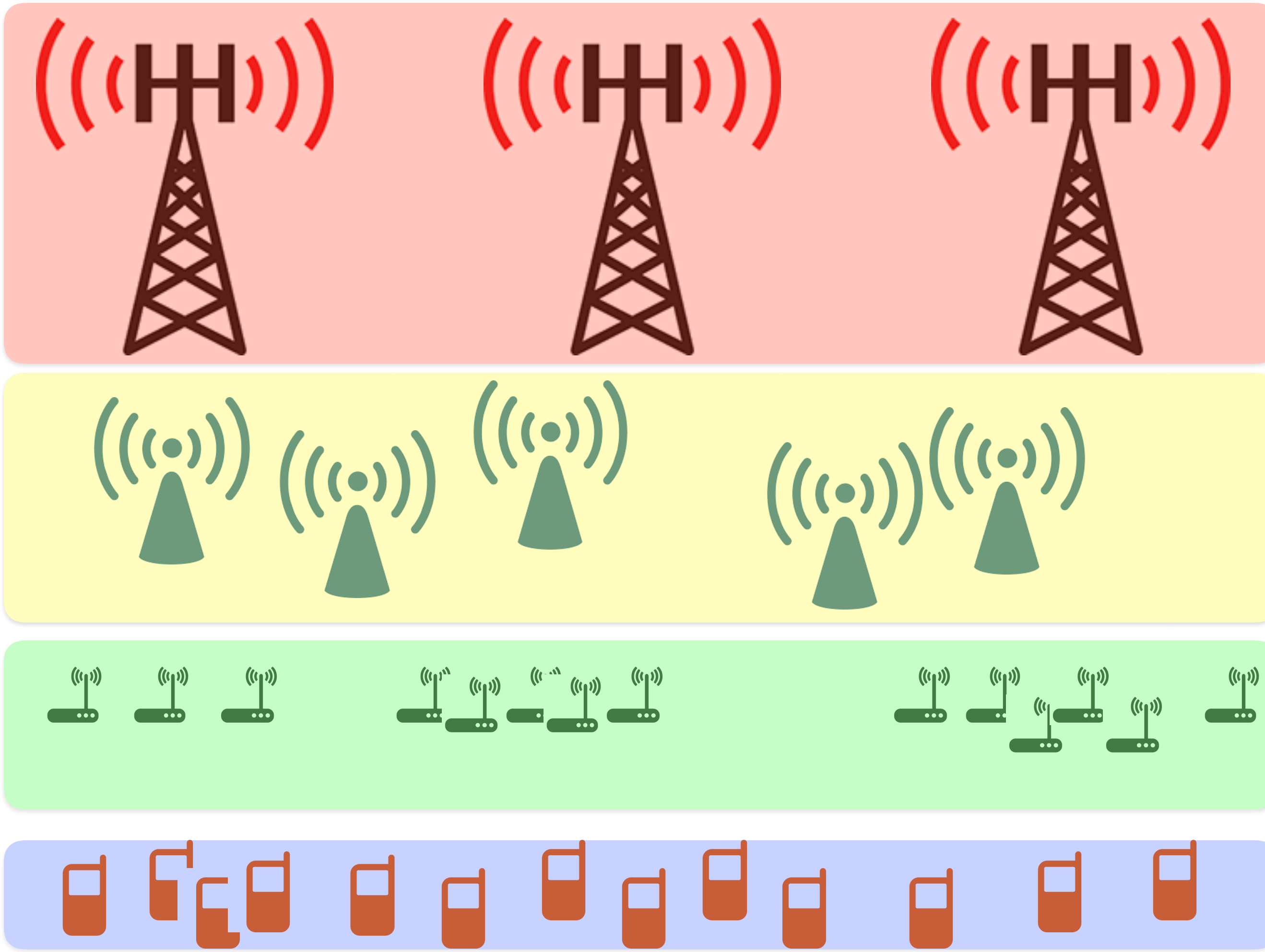

- 5G should significantly expand the performance targets in (at least) these three directions.

# The Three Axes of 5G



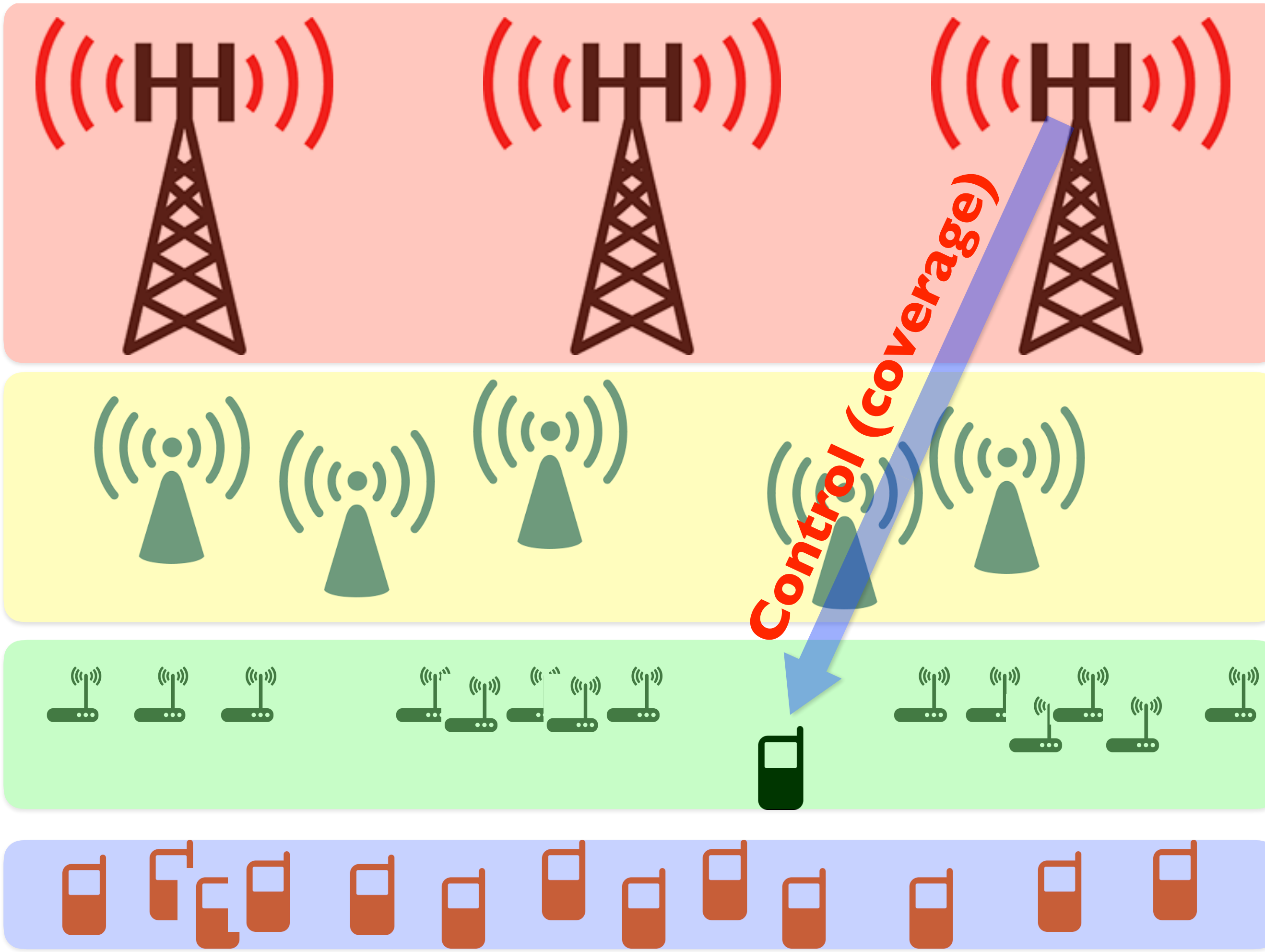

- 5G will significantly expand the performance targets in (at least) these three directions.
- We specifically focus on eMBB.

# Coming of Age for HetNets



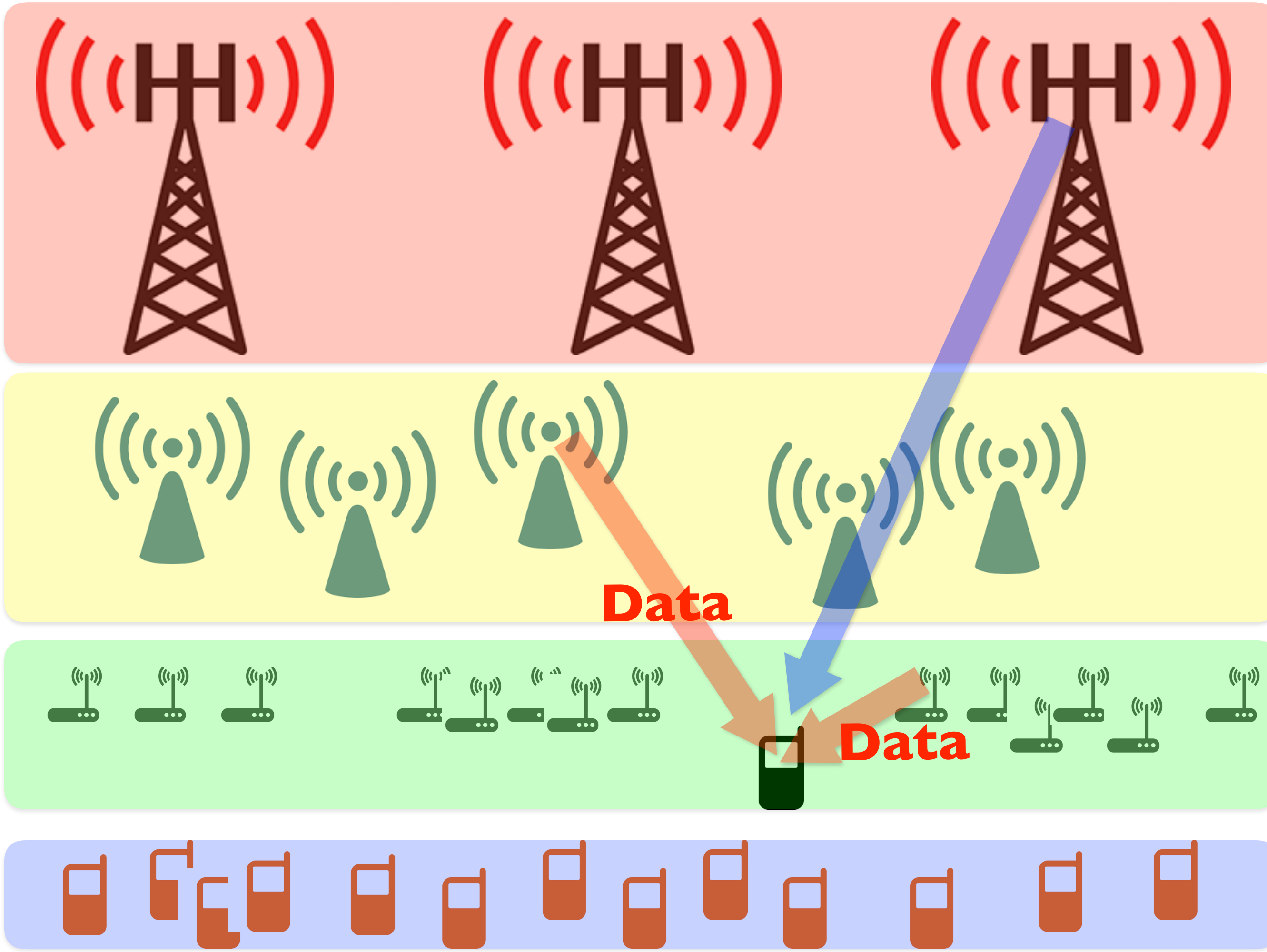
- A "rainforest" network architecture: concentrate bandwidth and resource where it is needed.

# Coming of Age for HetNets




- A “rainforest” network architecture: control plane for coverage.

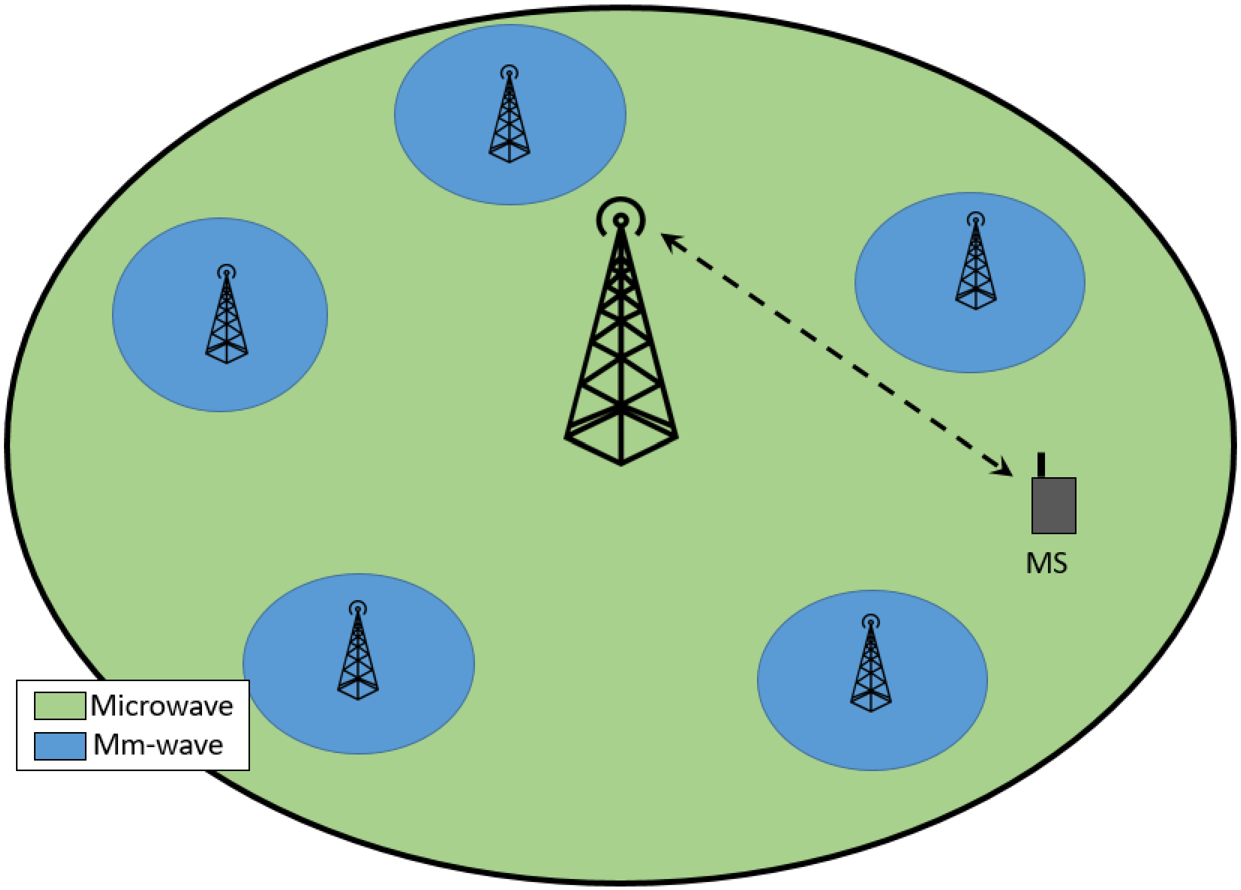
# Coming of Age for HetNets



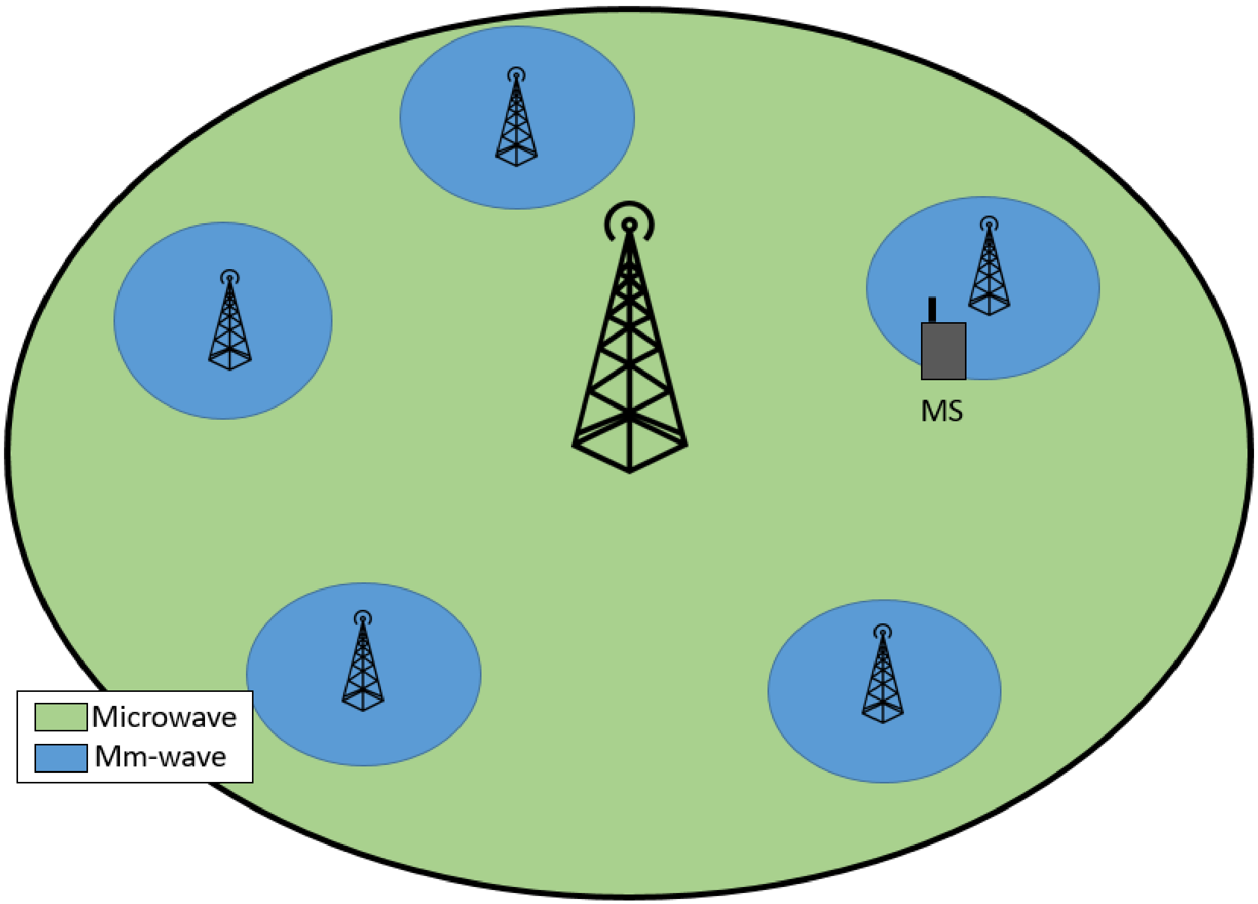

- A "rainforest" network architecture: data plane via local high-rate access.

# The Beam Alignment Problem

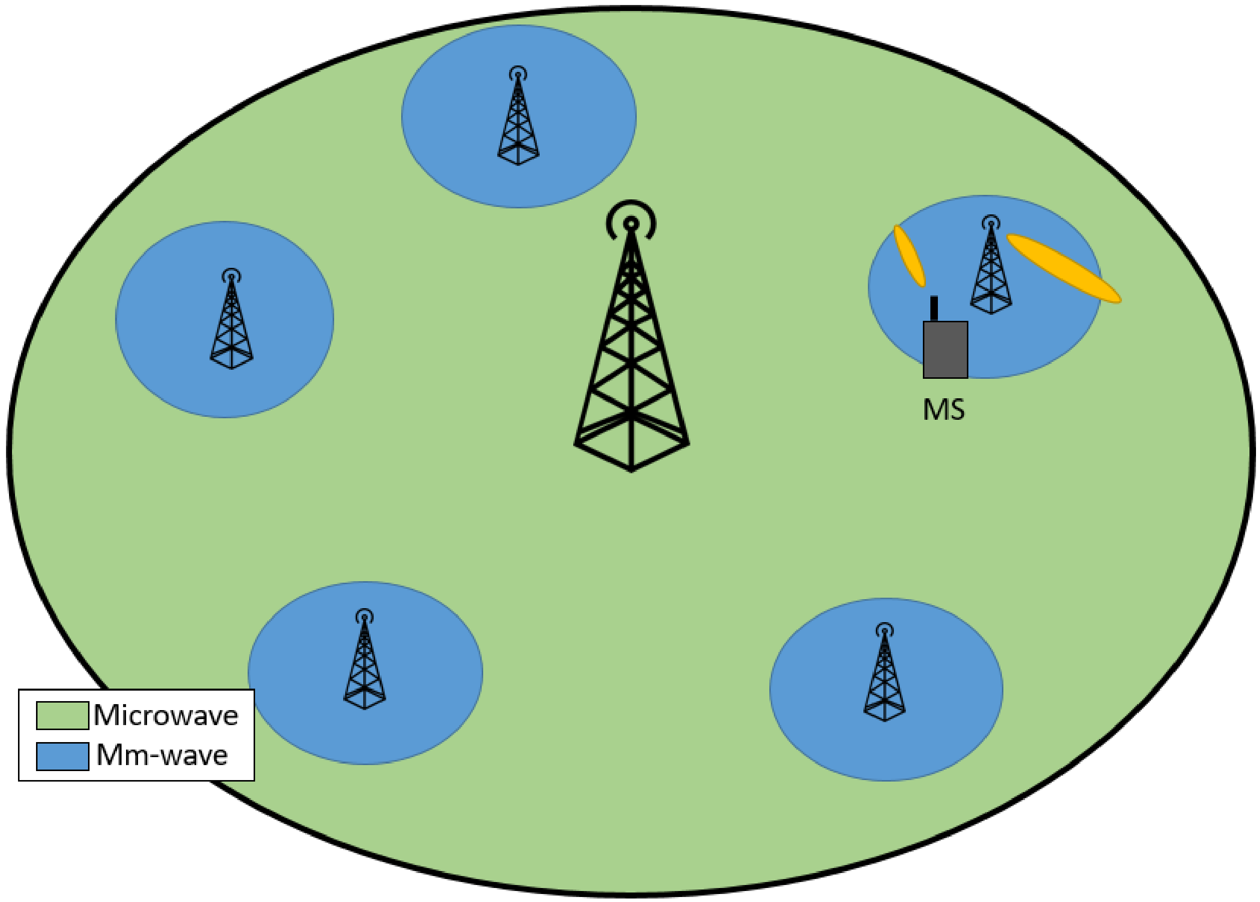




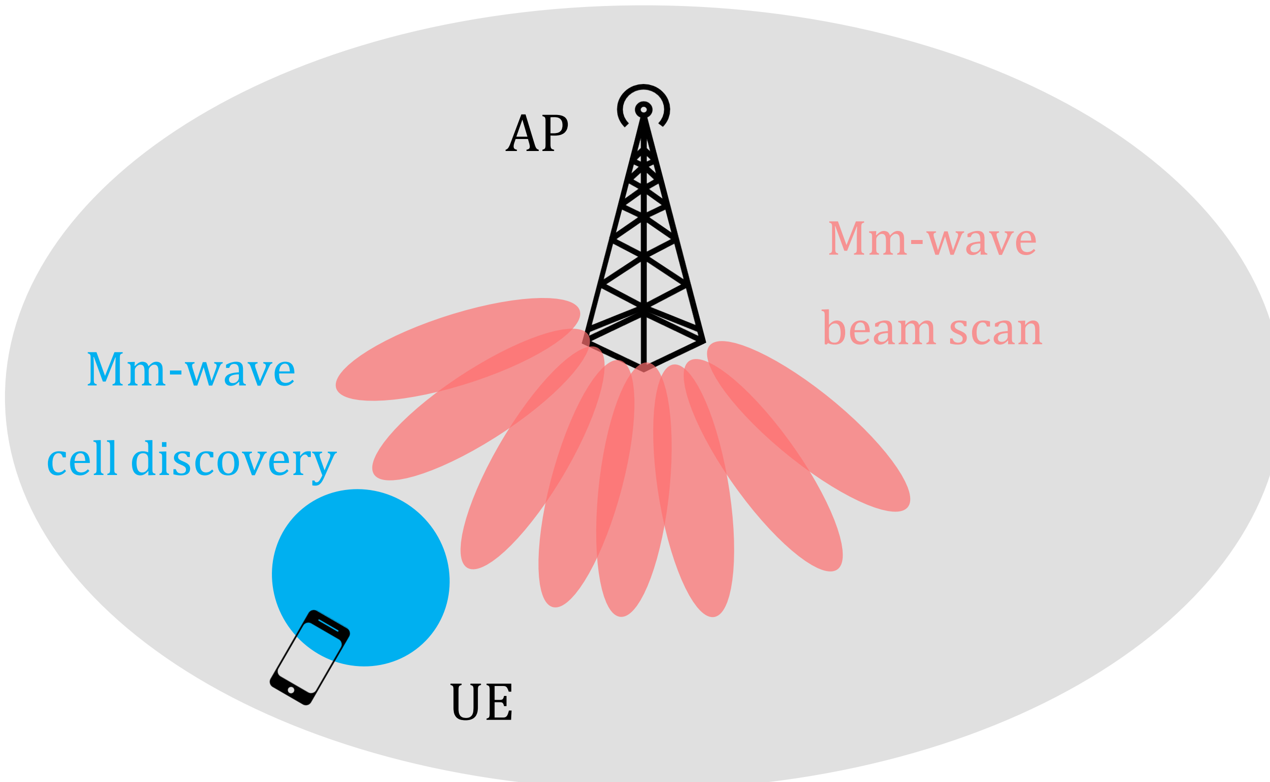
# The Beam Alignment Problem



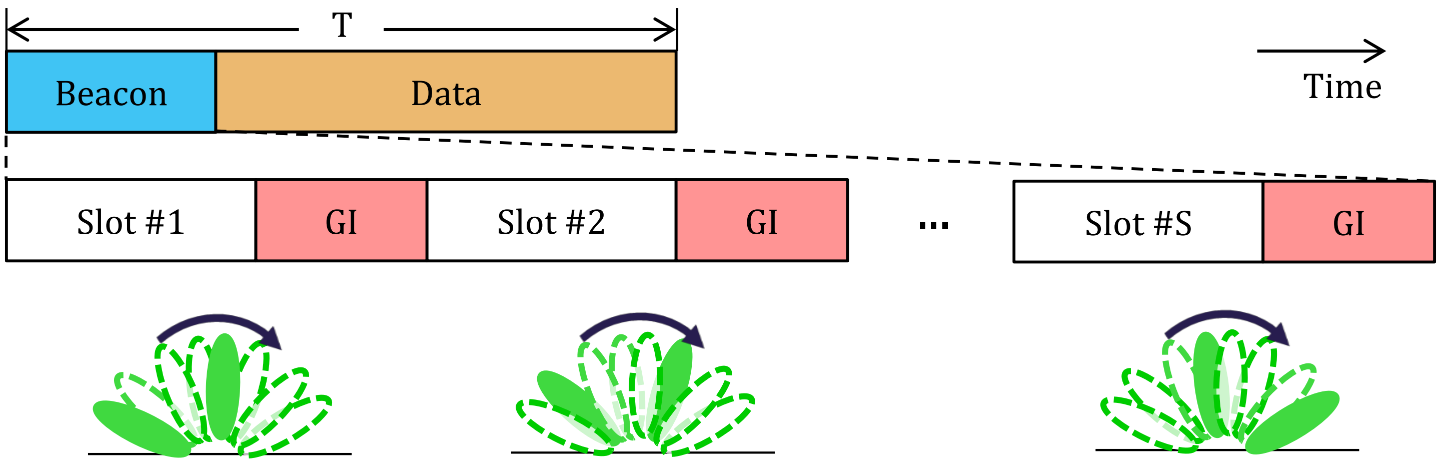
# The Beam Alignment Problem



# Current Approach: Beam Sweeping

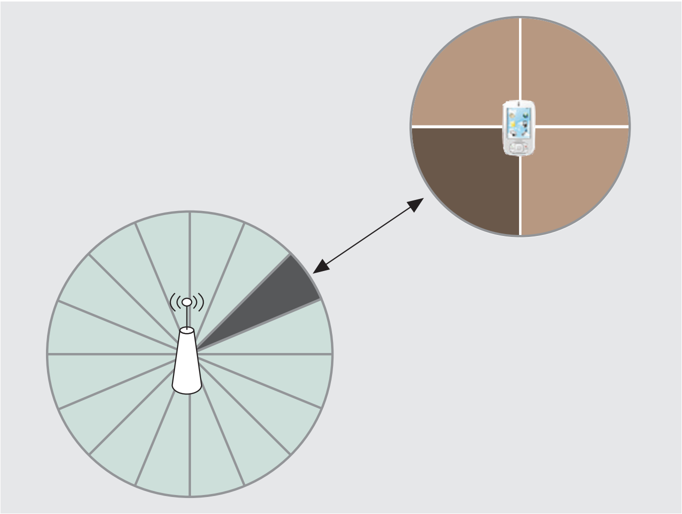


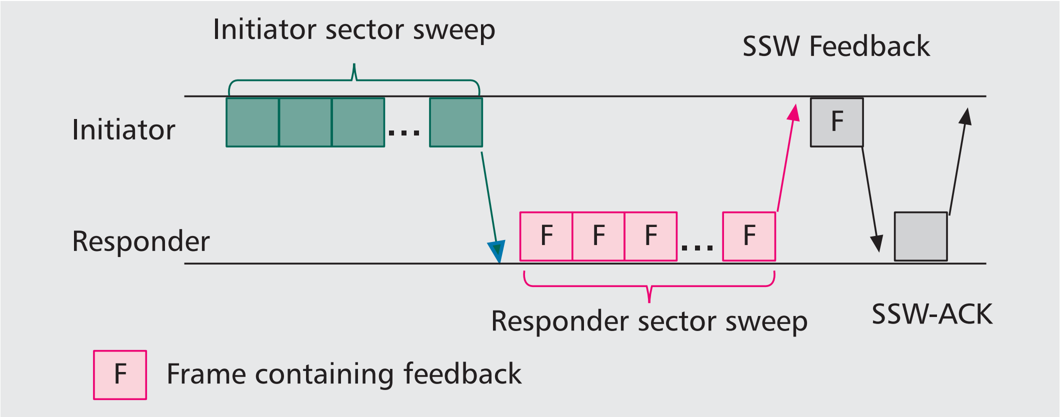
# Current Approach: Beam Sweeping




- The UE is essentially omnidirectional.
- What if BF gain and directional Tx/Rx is required also at the UE?

# Current Approach: Beam/Sector Sweeping

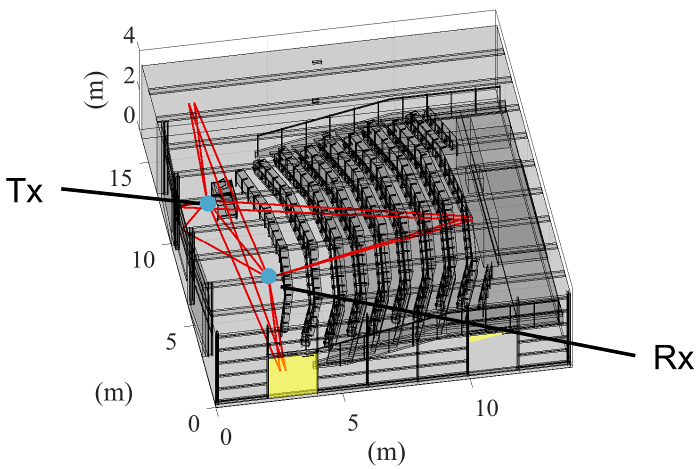




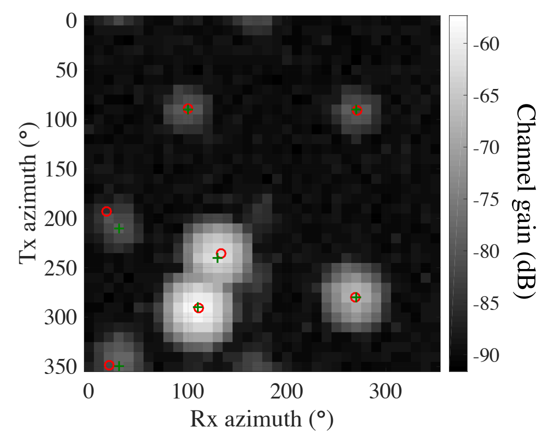

- Sector sweeping with interactive refinement (bisection).

# Sparsity in the Angle-Doppler-Delay Domain





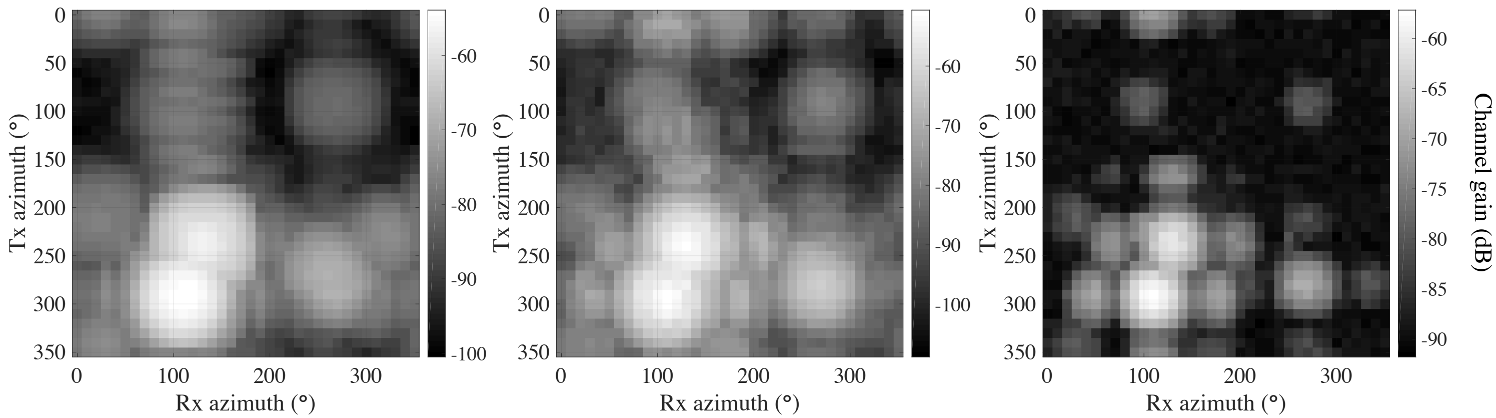

Simulated paths




Measured power-angular spectrum
Crosses: measured paths
Circles: simulated paths

* courtesy of Bile Peng, PhD Dissertation, TU Braunschweig, 2018

# Sparsity in the Angle-Doppler-Delay Domain

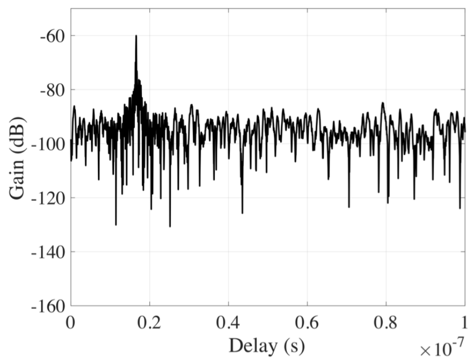



5-13 GHz    60-68 GHz    300-308 GHz

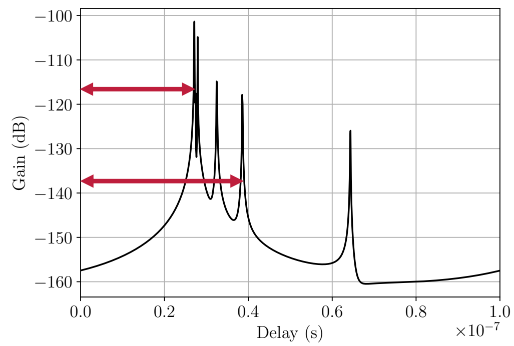
* courtesy of Bile Peng, PhD Dissertation, TU Braunschweig, 2018

# Sparsity in the Angle-Doppler-Delay Domain

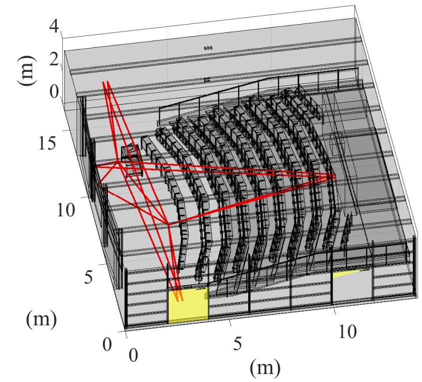





Measured CIR with channel sounder




Simulated CIR




Propagation paths

* courtesy of Bile Peng, PhD Dissertation, TU Braunschweig, 2018

# “Coherent” Compressed Sensing Approach

- The $N \times M$ channel matrix time-varying impulse response can be written as

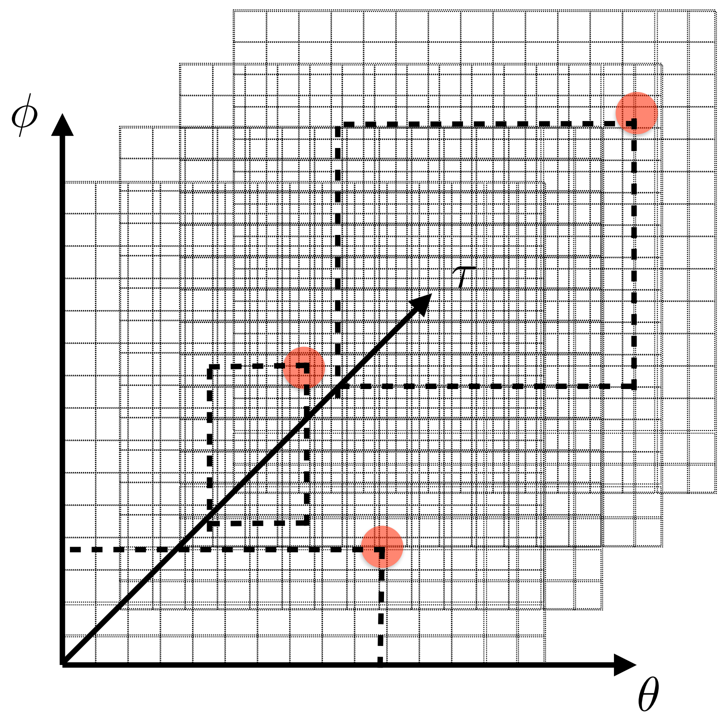
$$\mathbf{H}(t,\tau) = \sum_{l=1}^{L} h_l \mathbf{b}(\phi_l)\mathbf{a}^{\mathsf{H}}(\theta_l)e^{j2\pi\nu_l t}\delta(\tau - \tau_l)$$

- Applying Fourier Transform w.r.t. the delay variable $\tau$ we have the time-varying channel matrix transfer function

$$\mathbf{H}(t,f) = \sum_{l=1}^{L} h_l \mathbf{b}(\phi_l)\mathbf{a}^{\mathsf{H}}(\theta_l)e^{j2\pi\nu_l t}e^{-j2\pi\tau_l f}$$

# “Coherent” Compressed Sensing Approach

- With suitable discretization of the 4-dim domain $(\theta, \phi, t, f)$ we arrive at an approximately sparse representation.
- Using pilot signals we take noisy measurements of such sparse channel and using compressed sensing we can estimate the channel with a relatively small number of pilot dimensions.



# “Coherent” Compressed Sensing Approach

- Sampling the channel in the dual domain:
  - Angle ⇔ antennas;
  - Delay ⇔ frequency;
  - Doppler ⇔ time.

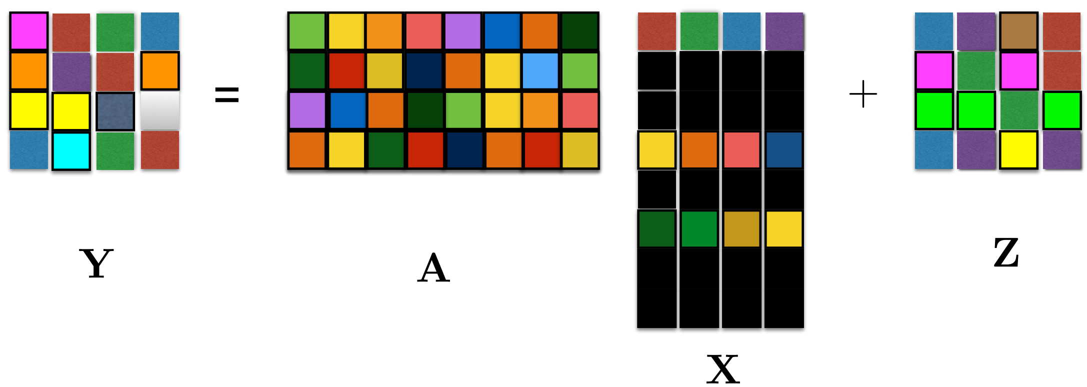
- Particular, for negligible Doppler we take measurements of the type:

$$y_{i,j,k}(t) = \mathbf{v}_j^{\mathsf{H}}(t)\mathbf{H}(t, k\Delta f)\mathbf{u}_j(t) + \text{noise}$$

where $\mathbf{u}_i, \mathbf{v}_j$ are beam probing directions and $k\Delta f$ is the $k$-th subcarrier of an OFDM grid.

# “Coherent” Compressed Sensing Approach

- Accumulating several of such measurements over several beacon time slots, one can form a so-called MMV problem (exploiting the fact that the sparsity support of the coefficient vectors remains the same over several time slots (common sparsity).




MMV: L_{2,1}-regularized Least Squares

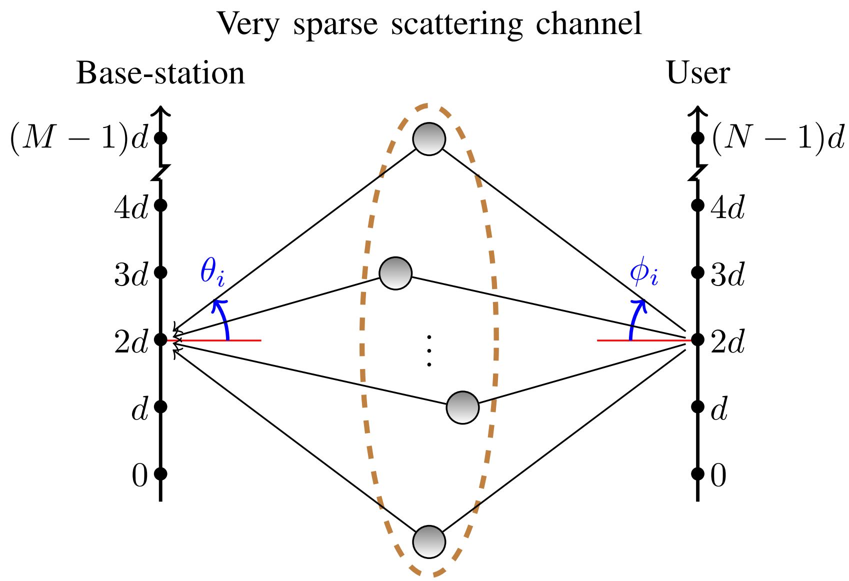
$$\min_{\mathbf{X}} \frac{1}{2} \|\mathbf{Y} - \mathbf{A}\mathbf{X}\|_2^2 + \lambda \|\mathbf{X}\|_{2,1}$$

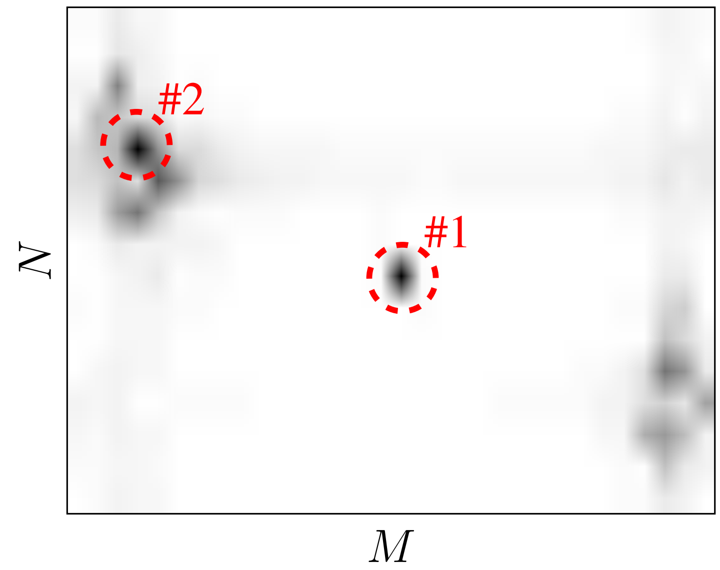
# Drawback of coherent CS

- Good sampling in the antenna domain implies nearly isotropic power spreading (no power directional concentration).
- It is difficult to implement with Hybrid Analog-Digital (HDA) beamforming.
- It is fragile to the time variations over the slots due to Doppler.
- The main problem is that it tries to do two things at the same time: guessing the right directions for BF and estimating the full channel matrix.

# Proposed Approach: Only Energy Measurements






- In order to identify the best AoA/AoD pair we need to find the peak of the two-dimensional scatter diagram (signal energy vs. angles).
- Delay and Doppler are irrelevant.
- After pointing the beams at both sides, the channel reduces to a single delay and Doppler shift, easily compensated by standard synch algorithms (timing and frequency estimation/compensation).

# Channel and signal model (1)

- Sparse AoA-AoD propagation: frequency-domain channel matrix at slot time $s$

$$\check{\mathsf{H}}_s(f) = \sum_{l=1}^{L} \rho_{s,l} \mathbf{b}(\phi_l) \mathbf{a}^{\mathsf{H}}(\theta_l) e^{-j2\pi f \tau_l}.$$

- Hybrid BF: $m$ Tx RF chains, $n$ Rx RF chains, OFDM discrete frequency $\{f_k = k\Delta f : k \in \mathcal{K}\}$

$$\begin{aligned} \check{y}_{s,i,j}[k] &= \frac{1}{\sqrt{n}} \mathbf{v}_{s,j}^{\mathsf{H}} \mathbf{H}_s[k] \mathbf{u}_{s,i} \check{x}_{s,i}[k] + \check{z}_{s,j}[k] \\ &= \frac{1}{\sqrt{n}} \sum_{l=1}^{L} \rho_{s,l} e^{-j2\pi k \tau_l \Delta f} g_{s,l,i}^{\mathrm{BS}} g_{s,l,j}^{\mathrm{UE}} \check{x}_{s,i}[k] + \check{z}_{s,j}[k]. \end{aligned}$$

- Channel-BF coupling coefficients: $g_{s,l,i}^{\mathrm{BS}} = \mathbf{a}^{\mathsf{H}}(\theta_l) \mathbf{u}_{s,i}$ and $g_{s,l,j}^{\mathrm{UE}} = \mathbf{v}_{s,j}^{\mathsf{H}} \mathbf{b}(\phi_l)$.

# Channel and signal model (2)

- Signal-to-Noise Ratio After Beamforming: $i$-th Tx data stream at the output of Rx RF chain $j$:

$$\text{SNR}_{\text{ABF}}^{(i,j)} = \frac{P_{\text{tot}} \sum_{l=1}^{L} \gamma_l |g_{s,l,i}^{\text{BS}}|^2 |g_{s,l,j}^{\text{UE}}|^2}{mnN_0B_i},$$

where $\gamma_l = \mathbb{E}[\rho_{s,l}|^2]$, $B_i$ is the bandwidth of the data signal $x_{s,i}(t)$ and we assume equal power allocation $P_{\text{tot}}/m$ per Tx stream.

- Signal-to-Noise Ratio Before Beamforming: as a reference we also define

$$\text{SNR}_{\text{BBF}} = \frac{P_{\text{tot}} \sum_{l=1}^{L} \gamma_l}{N_0B}.$$

# Virtual beamspace representation (1)

- We define the angular grids $\Theta$ and $\Phi$ and use the corresponding array responses as a discrete dictionary to represent the channel.
- For the ULAs (considered in this paper), after suitable normalization the dictionaries correspond to the columns of the unitary DFT matrices $\mathbf{F}_M$ and $\mathbf{F}_N$.
- The the beamspace representation of the channel matrix is given by $\mathbf{H}_s[k] = \mathbf{F}_N \check{\mathbf{H}}_s[k] \mathbf{F}_M^{\mathsf{H}}$, where

$$\check{\mathbf{H}}_s[k] = \sum_{l=1}^{L} \rho_{s,l} e^{-j2\pi k \tau_l \Delta f} \check{\mathbf{b}}(\phi_l) \check{\mathbf{a}}^{\mathsf{H}}(\theta_l),$$

and $\check{\mathbf{a}}(\theta_l) := \mathbf{F}_M^{\mathsf{H}} \mathbf{a}(\theta_l)$, $\check{\mathbf{b}}(\phi_l) := \mathbf{F}_N^{\mathsf{H}} \mathbf{b}(\phi_l)$ are the transformed array response vectors in the beamspace domain.

# Virtual beamspace representation (2)

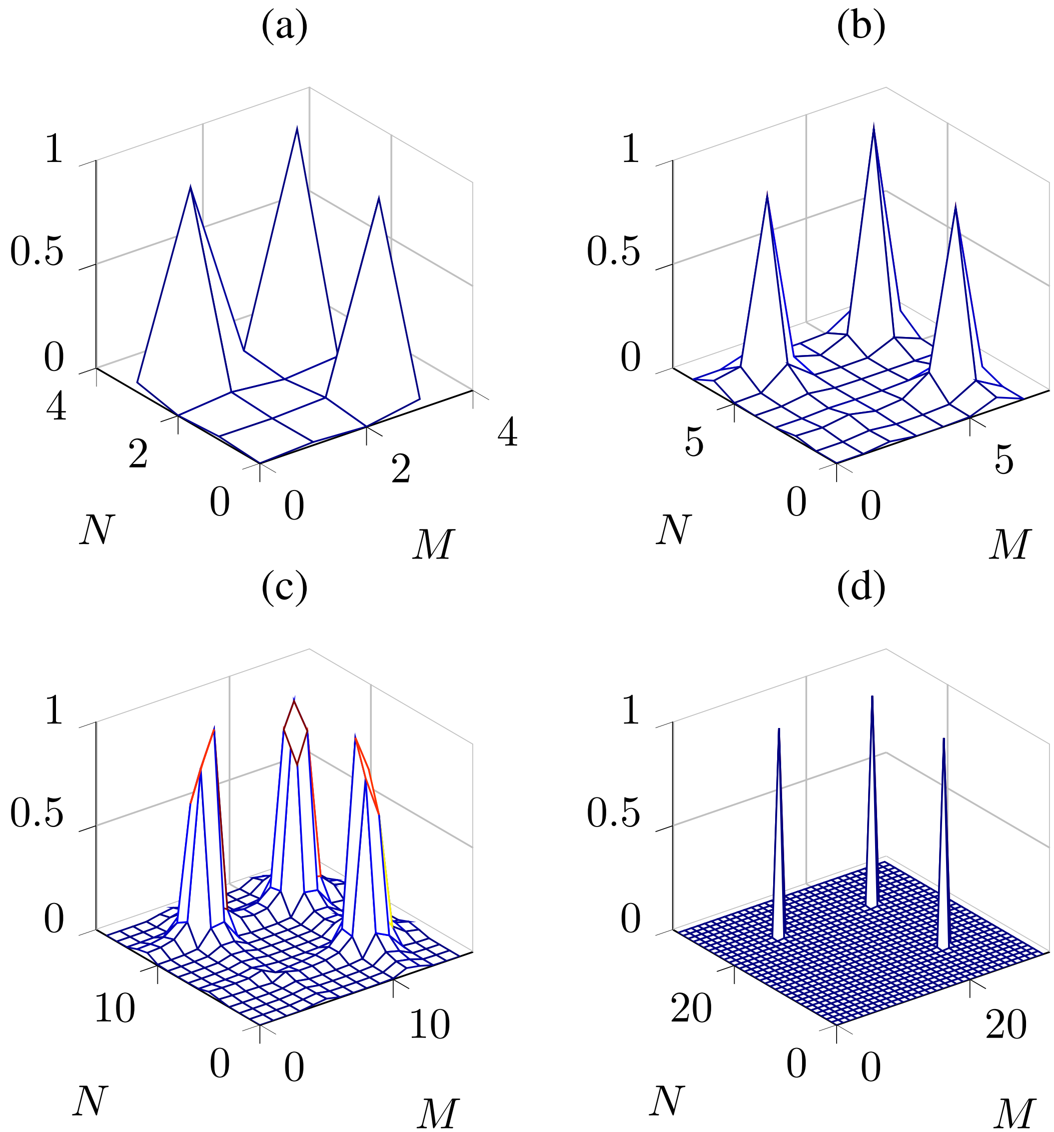
- The $m'$-th entry of $\check{\mathbf{a}}(\theta_l)$ is given by

$$[\check{\mathbf{a}}(\theta_l)]_{m'} = \frac{1}{\sqrt{M}} \frac{\sin(\pi \psi_l M)}{\sin(\pi \psi_l)} e^{-j\pi\psi_l(M-1)},$$

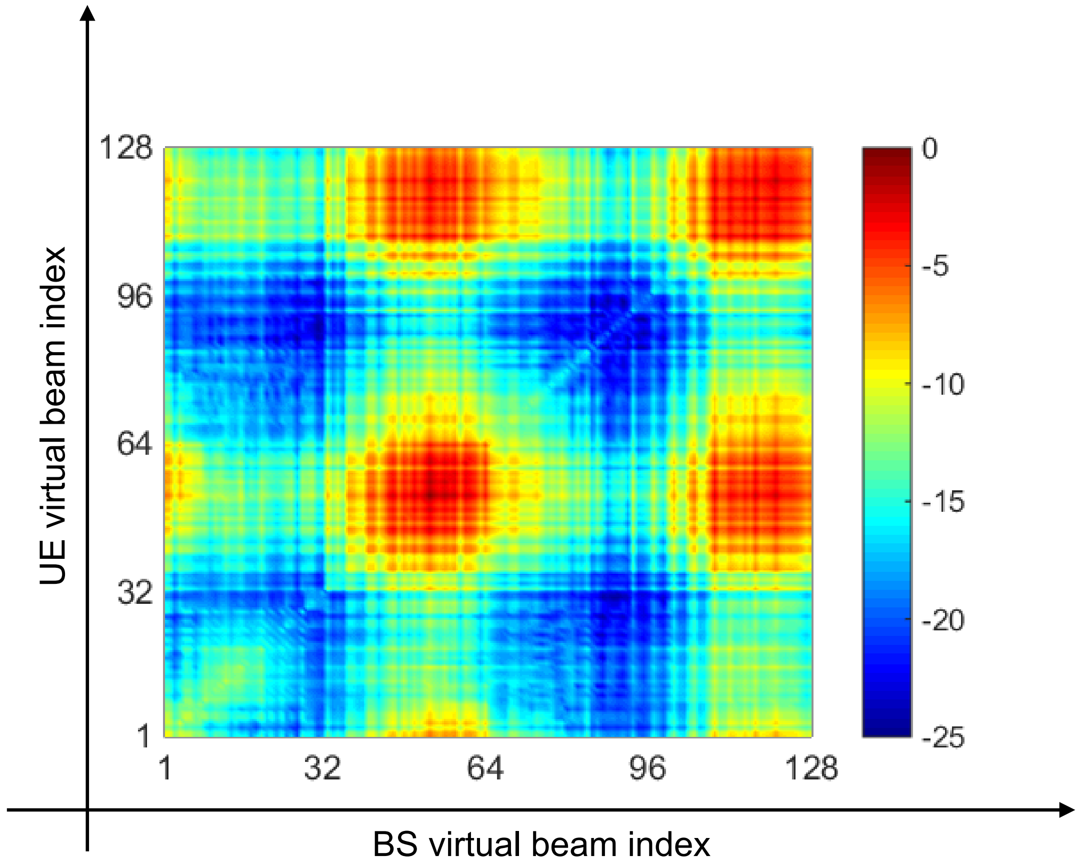
where $\psi_l = \left(\frac{m'-1}{M} - \frac{1}{2}\sin(\theta_l) - \frac{1}{2}\right)$. The magnitude $|[\,\check{\mathbf{a}}(\theta_l)\,]_{m'}|$ is localized around $\theta_l = \sin^{-1}[\frac{2(m'-1)}{M} - 1]$ with a width of $\approx \frac{1}{M}$.

- In general, as $M$ and $N$ grow, this channel representation becomes more and more sparse: $\check{\mathbf{H}}_s[k]$ contains significant components only for the directions $(k', k)$ corresponding to a strong MPC (coupled AoA-AoD directions).

# Virtual beamspace representation (3)



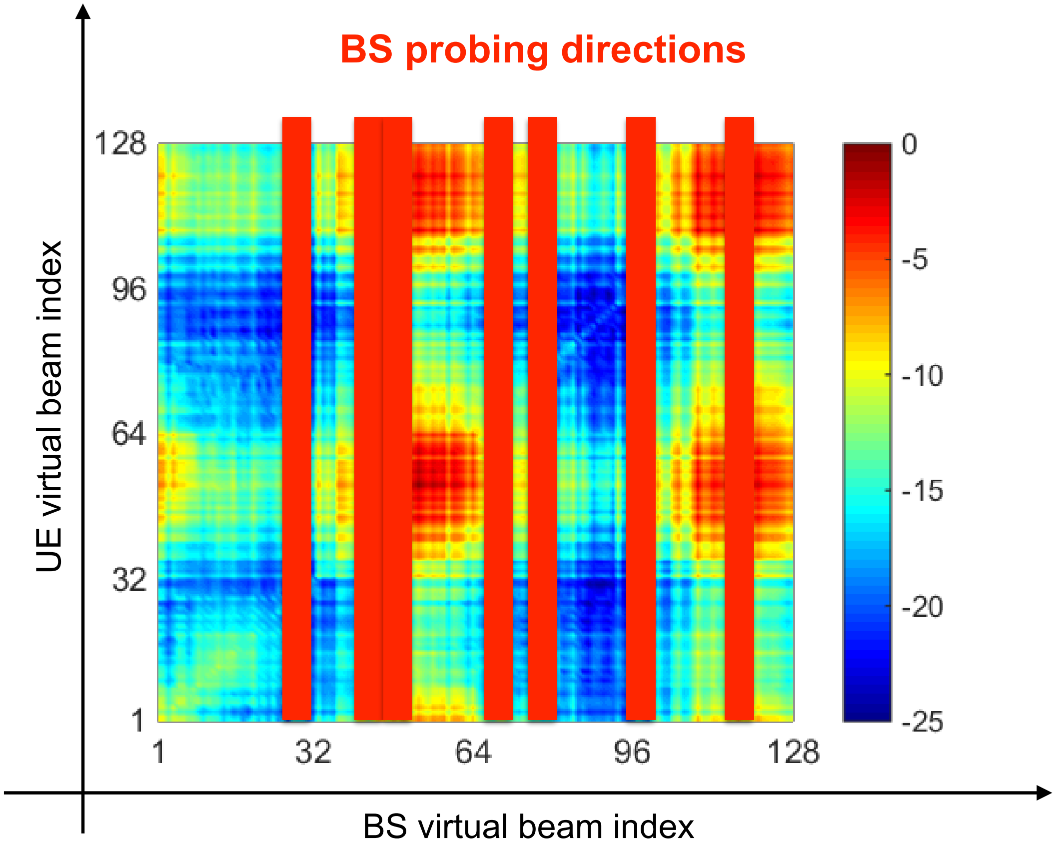
# Proposed scheme: main idea




- We wish to identify the strongly coupled AoA-AoD pair(s).

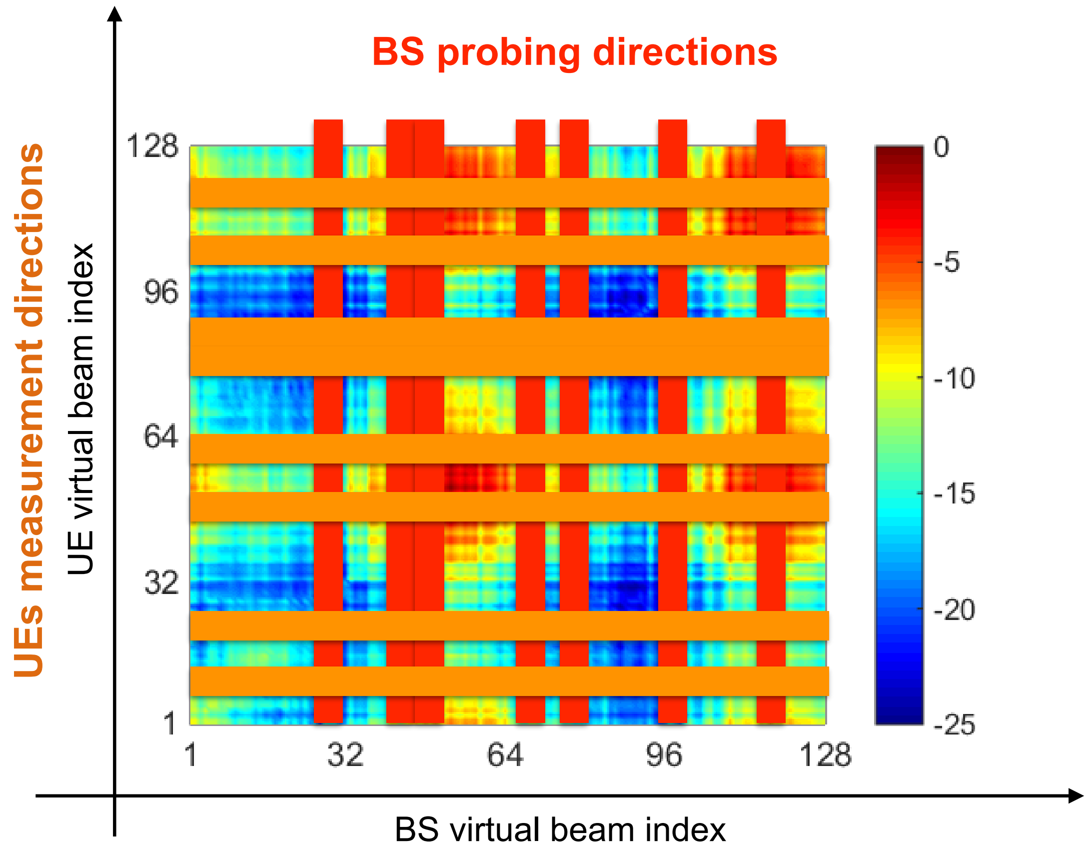
# Proposed scheme: main idea





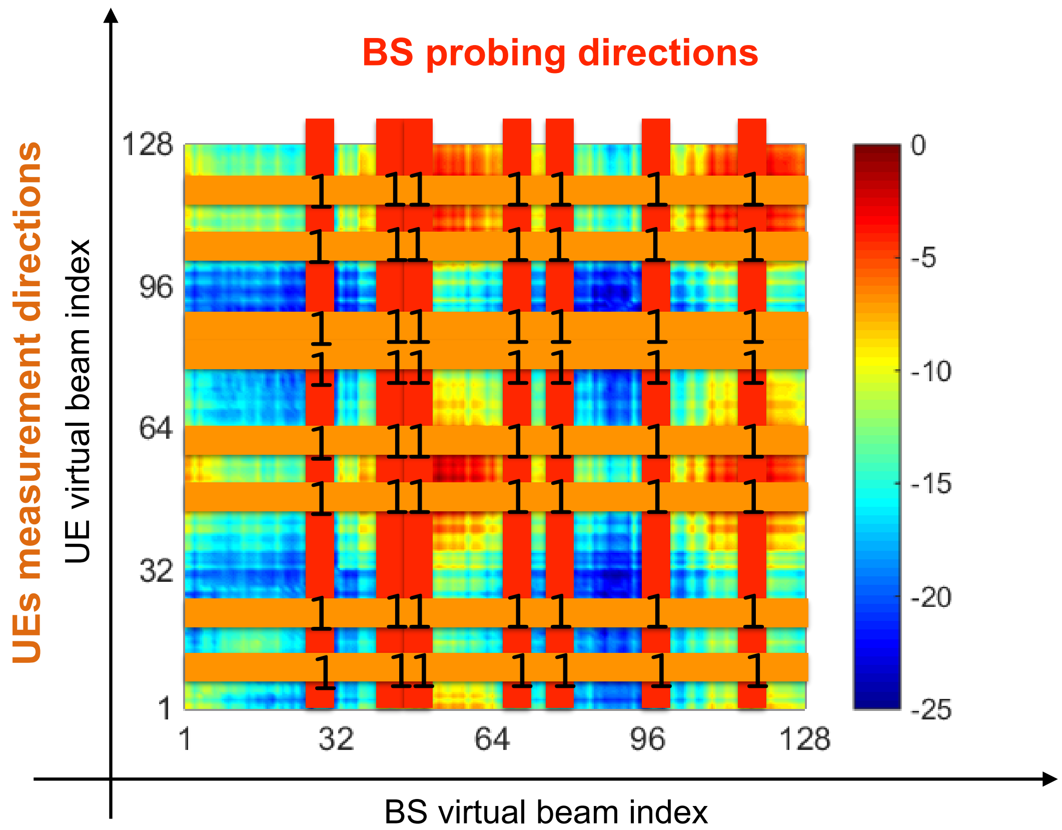

- We form an energy measurement by sending signal energy in randomly chosen directions....

# Proposed scheme: main idea



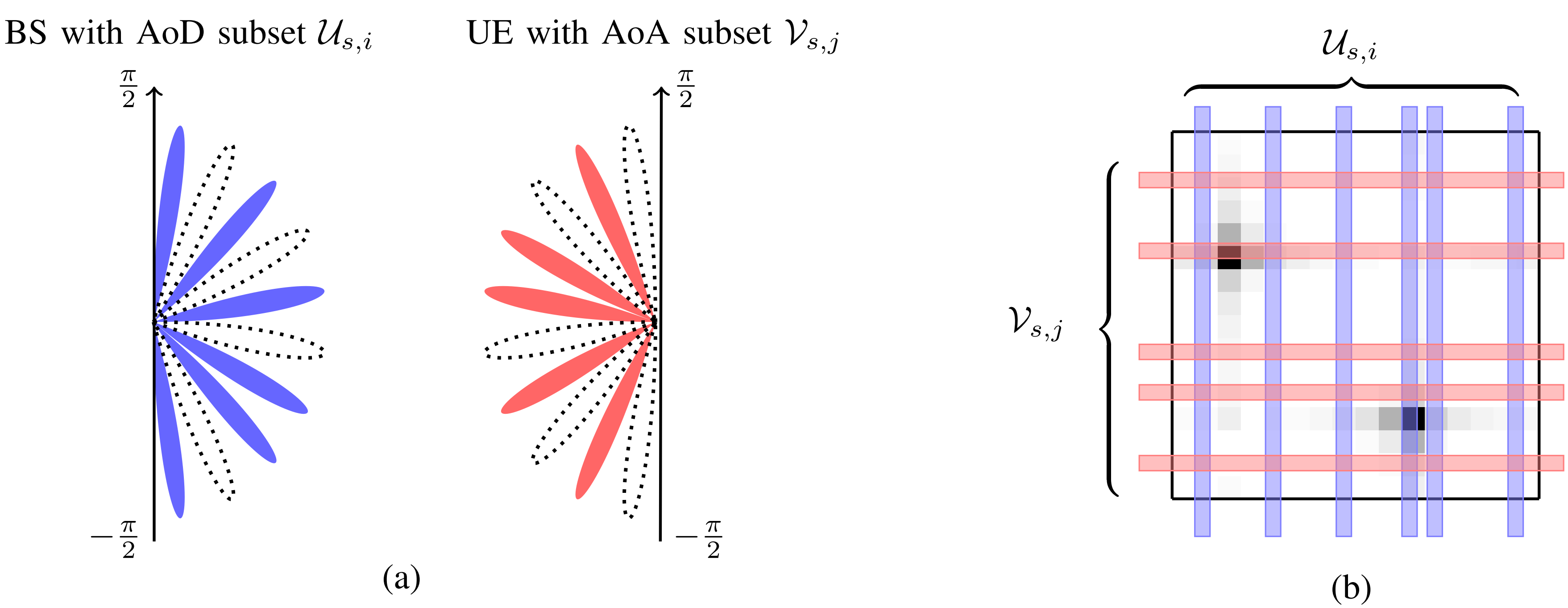

- .... and collecting the signal from randomly chosen directions.

# Proposed scheme: main idea




- Each Tx-Rx pattern forms a measurement ... we collect sufficiently many of such measurements.

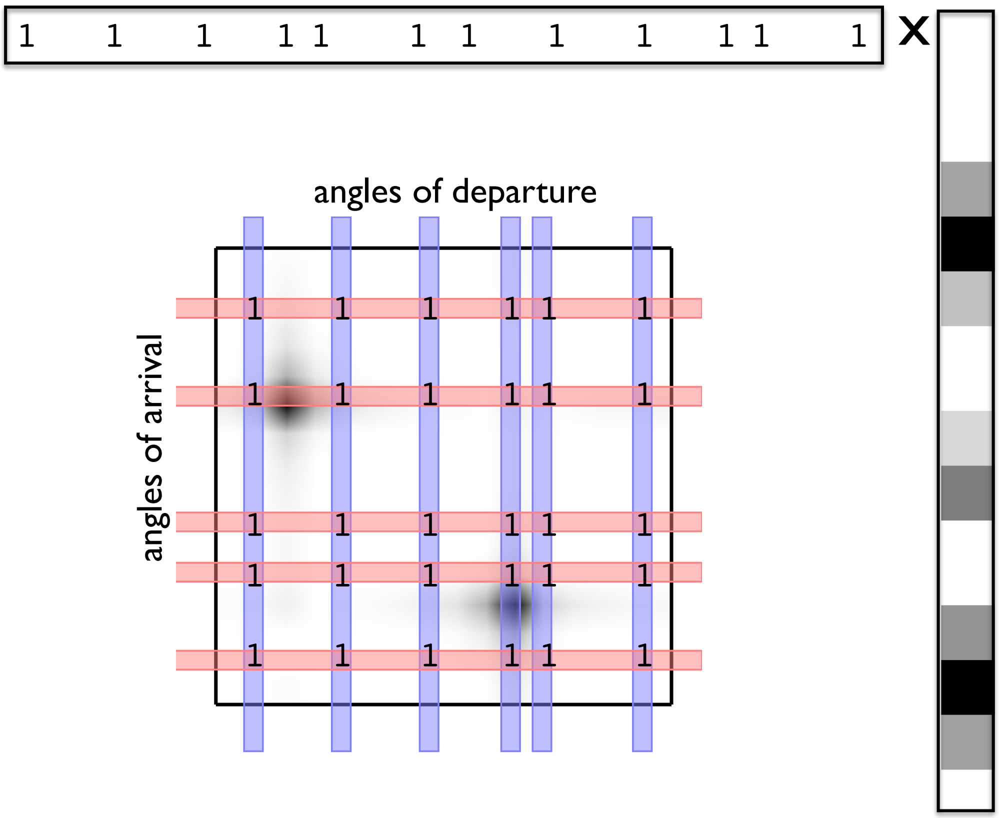
# Proposed scheme: main idea




- At each beacon slot, the BS sends a pseudo-random multi-finger beam pattern, and the users listen with their own pseudo-random multifinger beam pattern.
- The BS needs not know the user patterns: estimation of the best AoA-AoD is completely user-centric.

# Proposed scheme: main idea

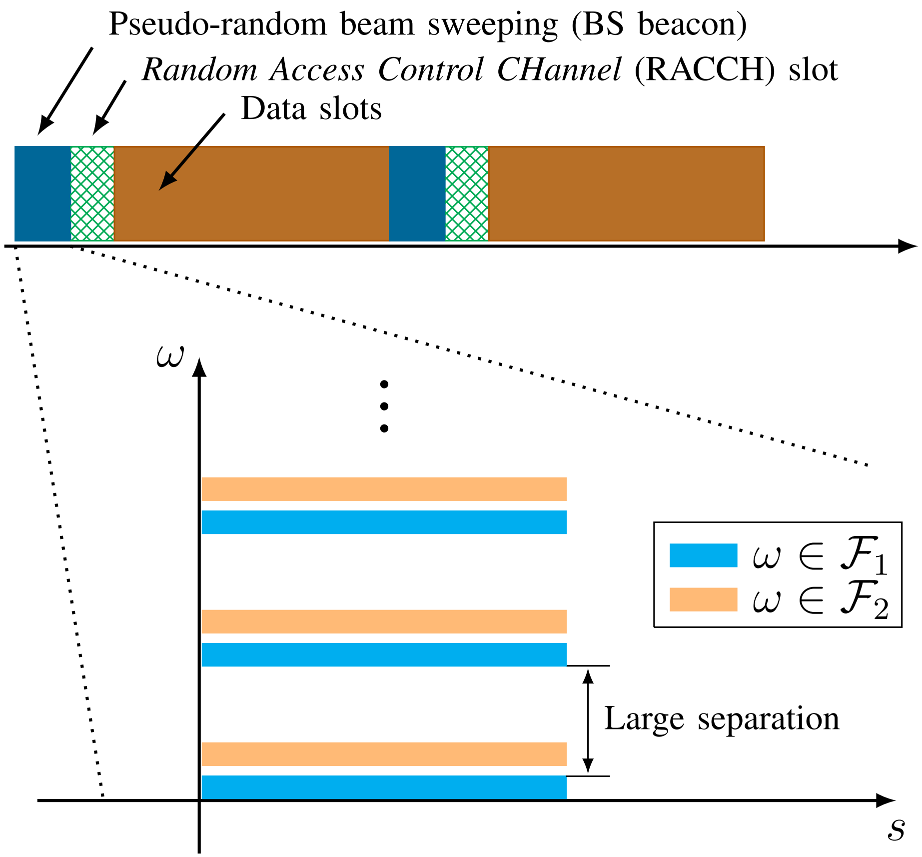


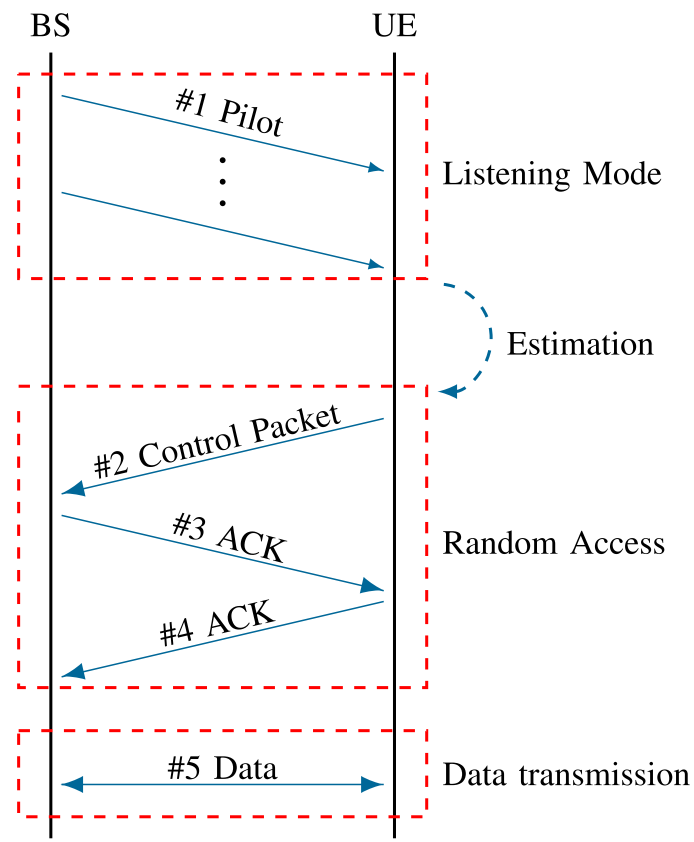



$$= \sum_{\ell=1}^{|\mathcal{V}_{s,j}||\mathcal{U}_{s,i}|} b_{s,\ell} g_\ell + w_s$$

- At each beacon slot, a measurement is generated, corresponding to the inner product of a binary 0-1 sensing vector with the vector of AoA-AoD channel strengths (the channel ASF).

# New scheme for fast and robust beam training



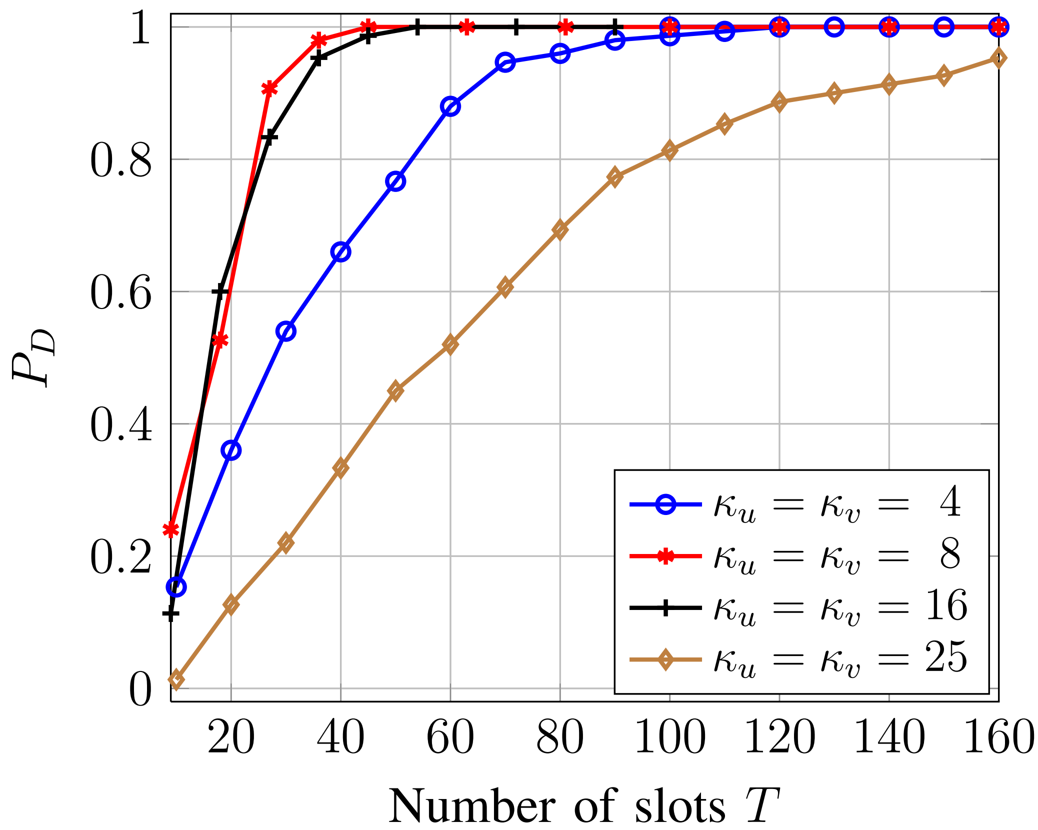
# NNLS Sparse Estimation

- After collecting $T$ measurements, the user solves the Non-Negative Least Squares (NNLS) given by

$$\widehat{\mathbf{g}} = \text{argmin}_{\mathbf{g}\in\mathbb{R}_+^{MN}} \|\mathbf{q} - \mathbf{B}\mathbf{g} - \sigma^2 \mathbf{1}\|^2$$

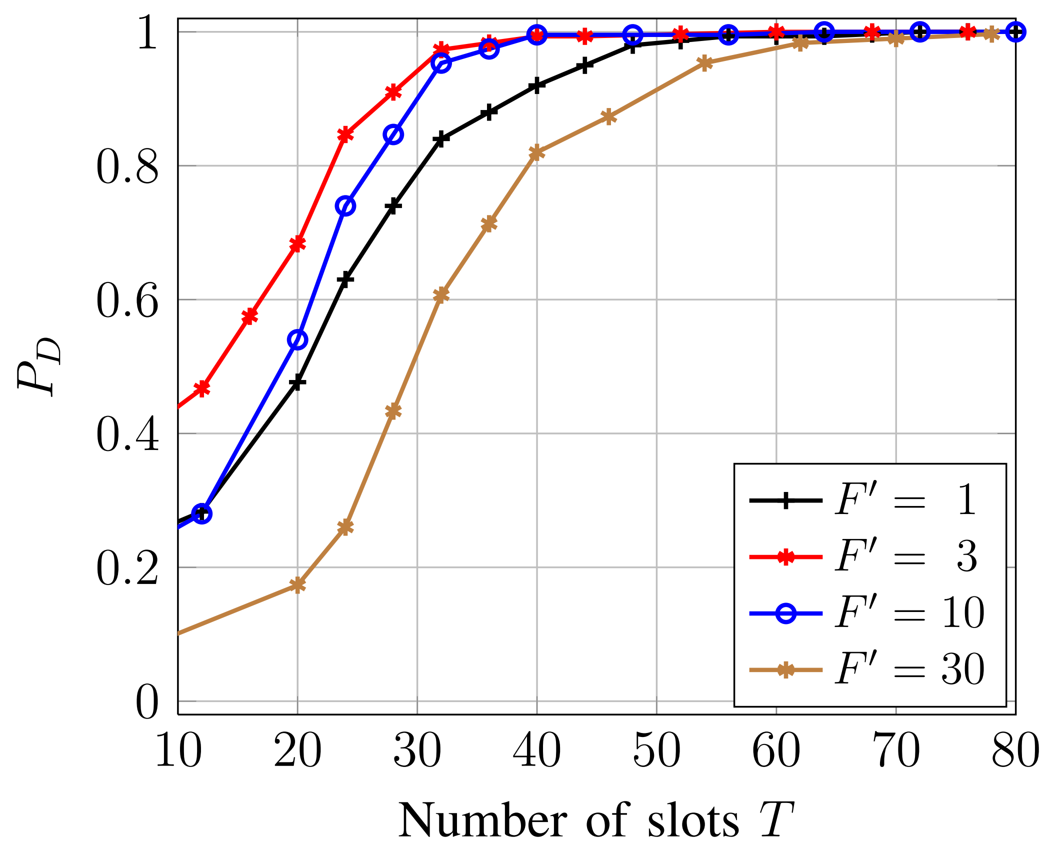
- NNLS promotes sparse solutions, even without the Lasso regularization.
- NNLS can be solved very efficiently by several techniques such as Gradient Projection, Proximal methods, etc.
  - R. Kueng and P. Jung "Robust nonnegative sparse recovery and the nullspace property of 0/1 measurements." *IEEE Trans. on Inform. Th.* Vol. 64, No. 2 (2018): 689-703.

# Numerical results (1)




- $N = M = 32$, $\text{SNR}_{\text{BBF}} = -33$ dB. Effect of spatial spreading.

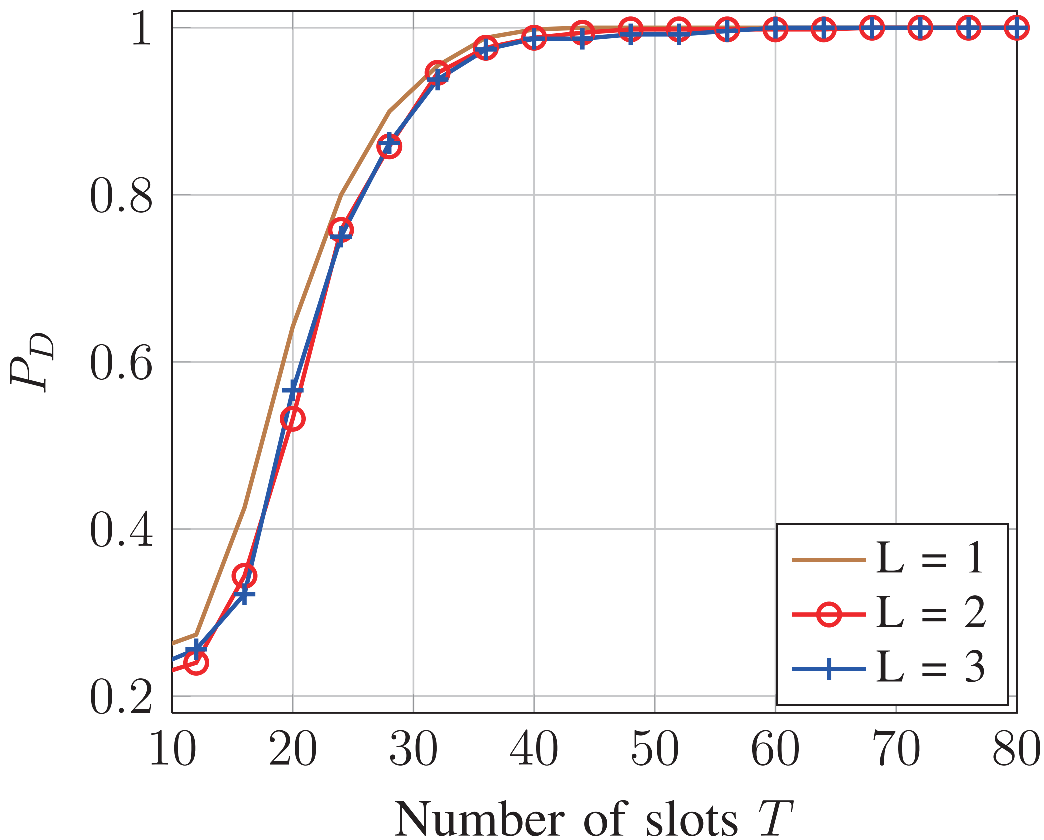
# Numerical results (2)




- $N = M = 32, \mathrm{SNR}_{\mathrm{BBF}} = -33$ dB. Effect of frequency-domain energy concentration.

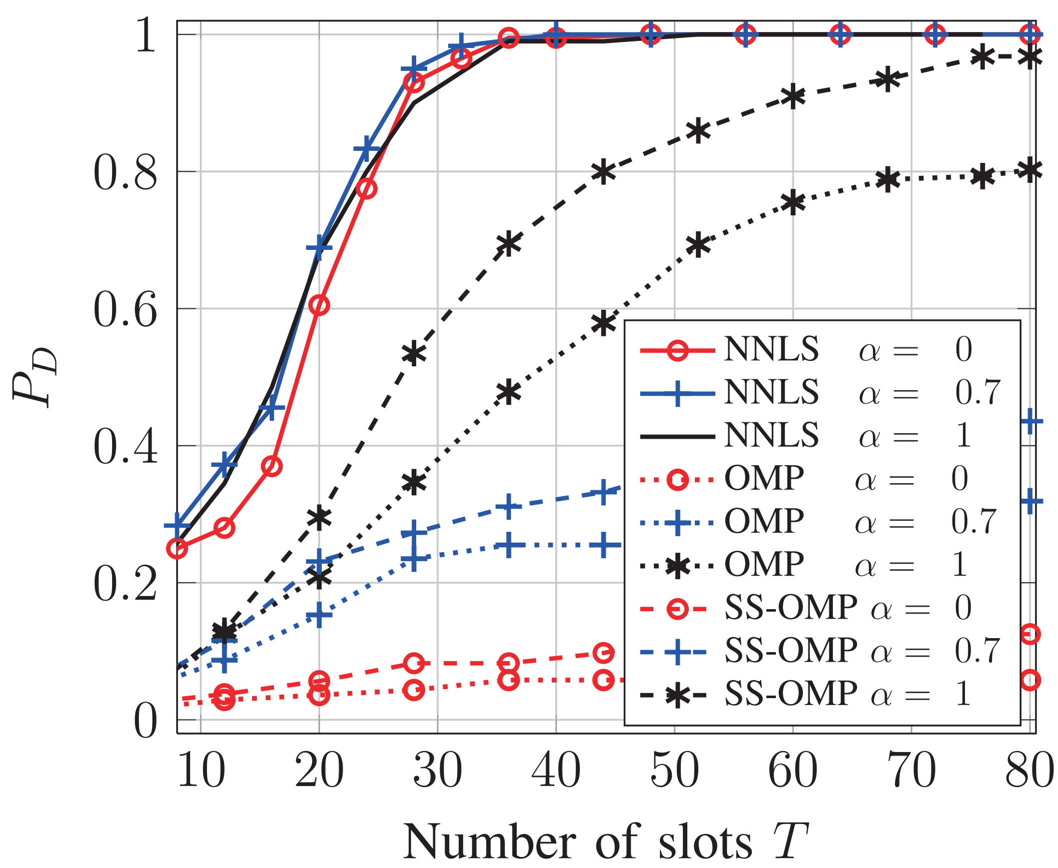
# Numerical results (3)





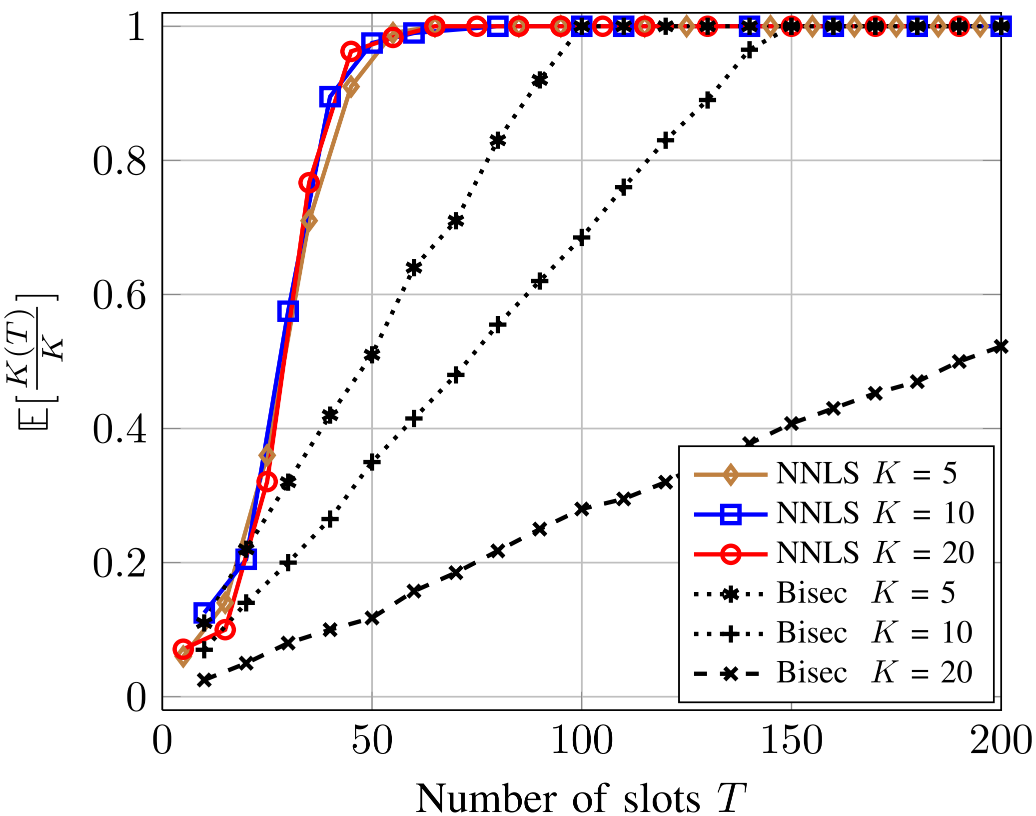

- $N = M = 32$, $\text{SNR}_{\text{BBF}} = -33$ dB. Robustness to number of MPCs.

# Numerical results (4)




- $N = M = 32$, $\mathrm{SNR}_{\mathrm{BBF}} = -33$ dB. Robustness to channel time-dynamics.

# Numerical results (5)




- $N = M = 32$, SNR$_{\text{BBF}} = -33$ dB. Scalability w.r.t. number of users.

# Single-Carrier Approach

- The idea is the same but the beacon probing signal is a single-carrier PN sequence instead of a comb of orthogonal frequencies.
- Advantage: more robust to high Doppler shifts.
- Format of the transmit beacon signal from the $i$-th BS antenna port (RF chains):

$$\mathbf{x}_{s,i}(t) = \sqrt{\frac{P_{\text{tot}} T_c}{m}} \mathbf{u}_{s,i} \left( \sum_{n=1}^{N_c} \varrho_{n,i} p_r(t - nT_c) \right)$$

# Single-Carrier Approach

- Received signal at the output of the $j$-th RF chain at the UE side is given by

$$\hat{y}_{s,j}(t) = \sum_{i=1}^{m} \sum_{l=1}^{L} \sqrt{E_{\rm dim}} \mathbf{v}_{s,j}^{\mathsf{H}} \mathbf{H}_{s,l}(t) \mathbf{u}_{s,i} x_{s,i}(t-\tau_l) + z_{s,j}(t),$$

- $E_{\rm dim} = \frac{P_{\rm tot} T_c}{mn}$ indicates the per-stream pilot chip energy distributed over the transmit and receive RF chains.

- Per-slot approximation of the channel: Doppler yields a rotating phase that changes (a little) over the chips sequence

$$\mathbf{H}_{s,l}(t)\Big|_{t \in [nT_c,(n+1)T_c)} \approx \rho_{s,l} e^{j2\pi(\check{\nu}_{s,l}+\nu_l n T_c)} \mathbf{b}(\phi_l) \mathbf{a}(\theta_l)^{\mathsf{H}} = \mathbf{H}_{s,l} e^{j2\pi \nu_l n T_c}$$

# Single-Carrier Approach

- As a result, the term $\mathbf{H}_{s,l}(t)x_{s,i}(t-\tau_l)$ can be written as

$$\mathbf{H}_{s,l}(t)x_{s,i}(t-\tau_l) = \mathbf{H}_{s,l}x^l_{s,i}(t-\tau_l)$$

where

$$x^l_{s,i}(t) = \sum_{n=1}^{N_c} \varrho_{n,i} e^{j2\pi\nu_l n T_c} p_r(t-nT_c)$$

is a (slightly) modified PN sequence due to the phase rotation of the chips.

- The receiver correlates each RF chain output $\hat{y}_{s,j}(t)$ with all the PN sequences $x_{s,i}(t)$ computing

$$y_{s,i,j}[k] = \int \hat{y}_{s,j}(\tau)x^*_{s,i}(\tau-kT_c)d\tau, \quad \text{for } k=0,\ldots,N_s-1$$

(normally we take $N_s = N_c + \frac{\Delta\tau_{\max}}{T_c}$).

# Single-Carrier Approach

- The measurement $(s, i, j)$ is obtained by summing over the $S$ repetitions of the PN sequence per beacon slot, the accumuklated output energy of the correlators (sum of squares of the output chip samples):

$$q_{s,i,j} = \frac{1}{S} \sum_{s'=1}^{S} \sum_{k=0}^{N_s-1} \left| y_{sS+s',i,j}[k] \right|^2$$

- It can be shown (after some tedious algebra) that $q_{s,i,j}$ has the same form of before (multiplication of the vectorized scattering matrix times a pattern of 0-1, plus error terms (signal $\times$ noise, and noise $\times$ noise).

- Eventually the same NNLS problem can be solved to estimate the angles of the strong MPCs.

# An example with QuaDriGa Channels

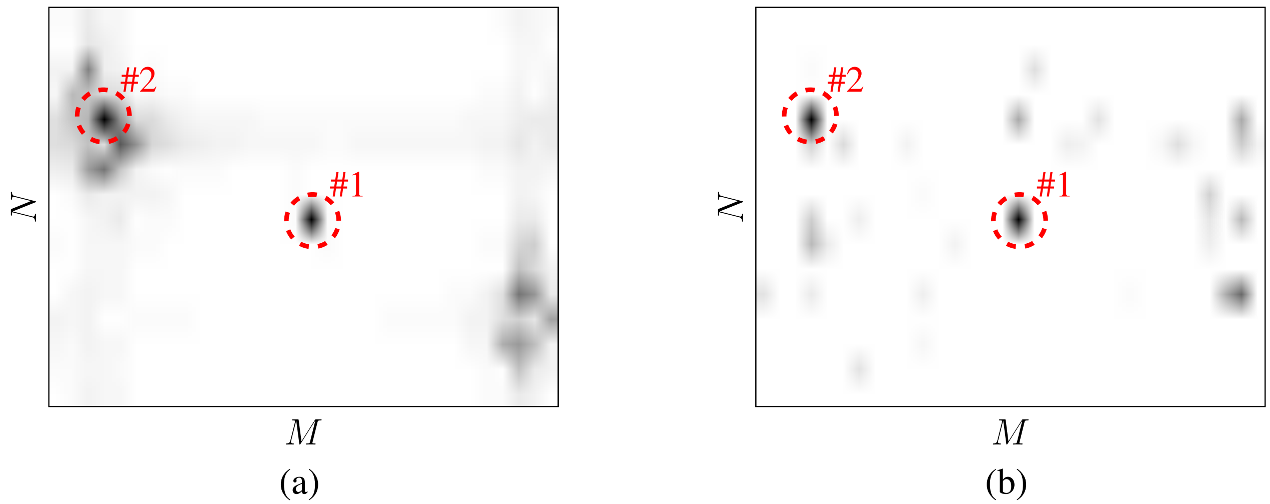
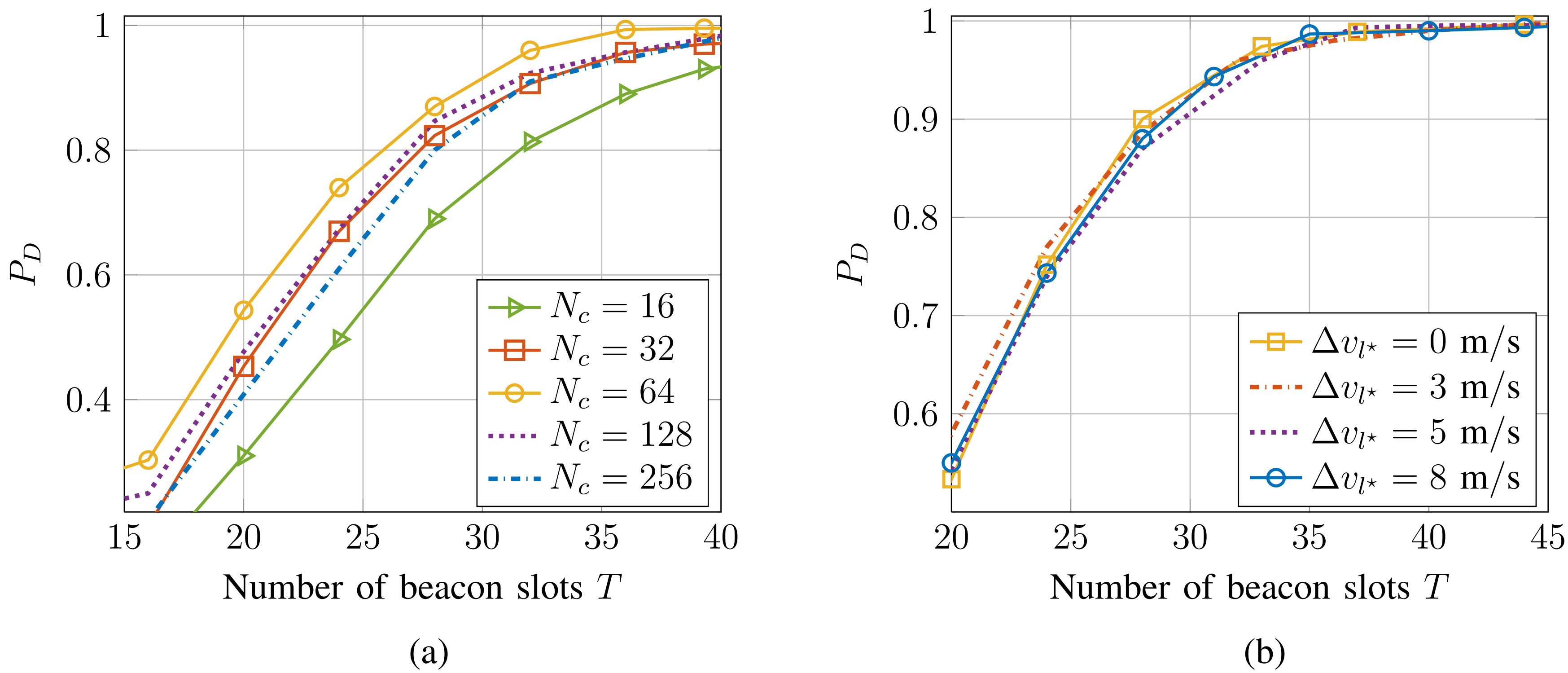
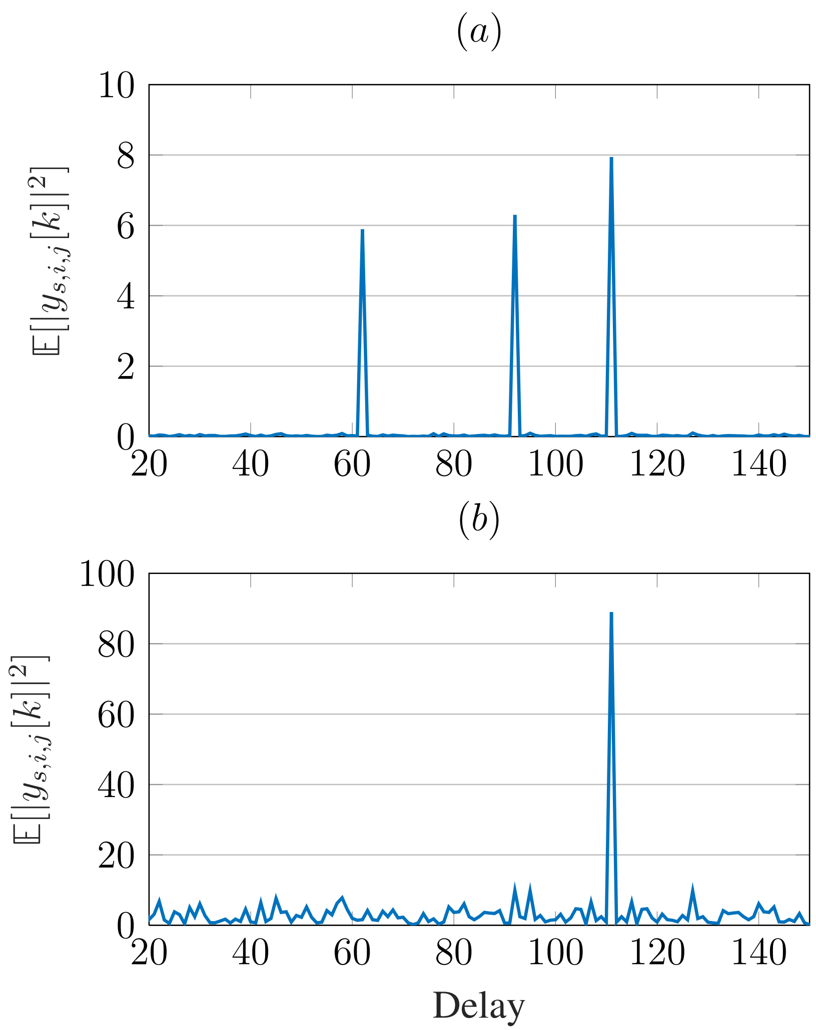



Fig. 4: Illustration of the second moments of the beam-domain channel matrix $\mathbf{\Gamma}_k$: (a) the actual QuaDRiGa generated $\mathbf{\Gamma}_k$, (b) the NNLS estimated $\mathbf{\Gamma}_k^\star$. The dashed circles indicate the top $p = 2$ strongest components in $\mathbf{\Gamma}_k$ and $\mathbf{\Gamma}_k^\star$, respectively. We announce a success in the BA phase if the locations of the strongest component in $\mathbf{\Gamma}_k$ and in $\mathbf{\Gamma}_k^\star$ are consistent.

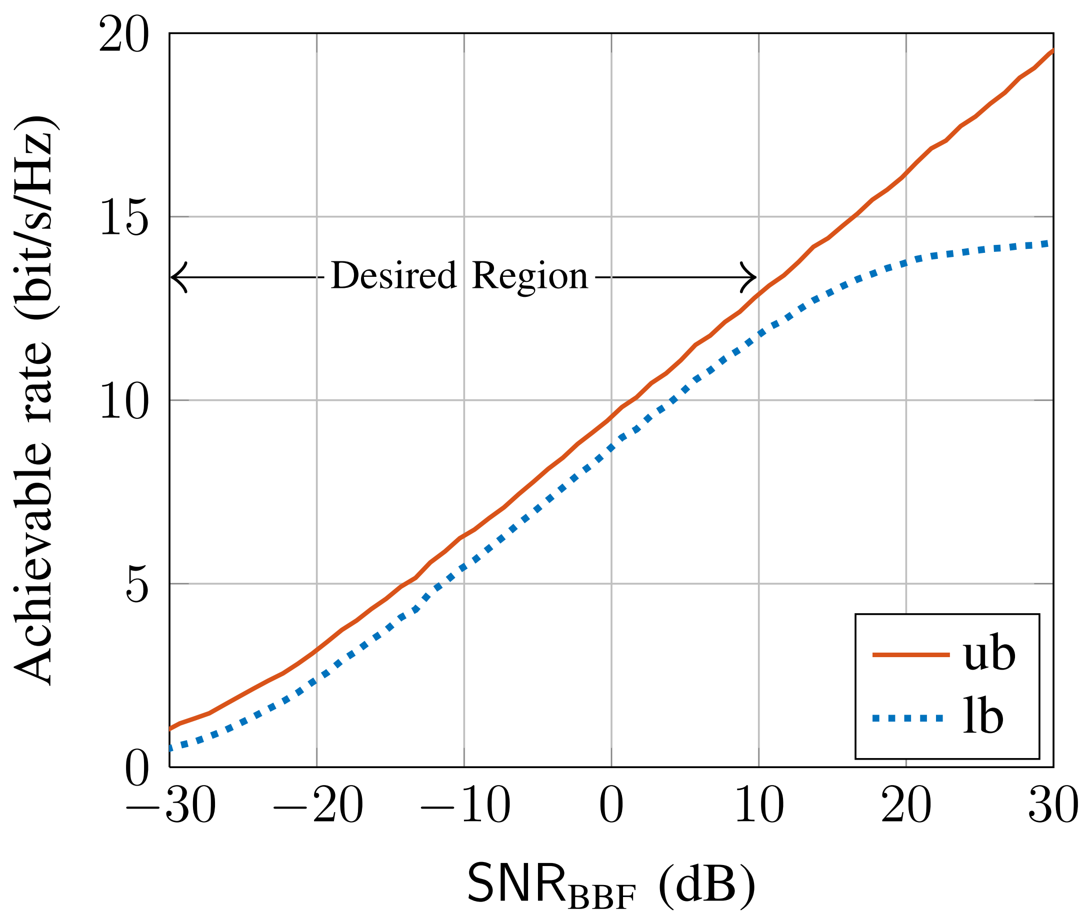
# Spreading Length and Robustness to Doppler

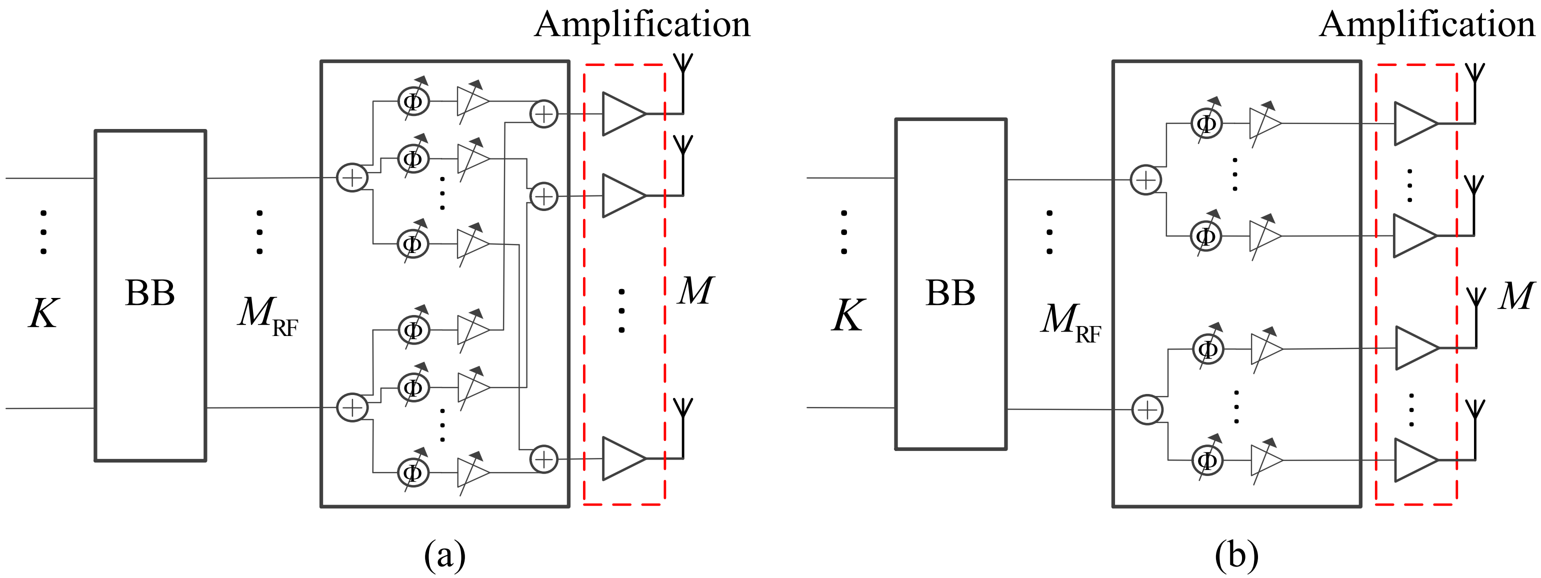


# A case for single-carrier in mmWaves (1)



# A case for single-carrier in mmWaves (2)






- The One-Stream-Per-Subarray (OSPS) architecture is modular, more energy-efficient, and significantly simpler in terms of hardware complexity.

# Effectiveness of OSPS

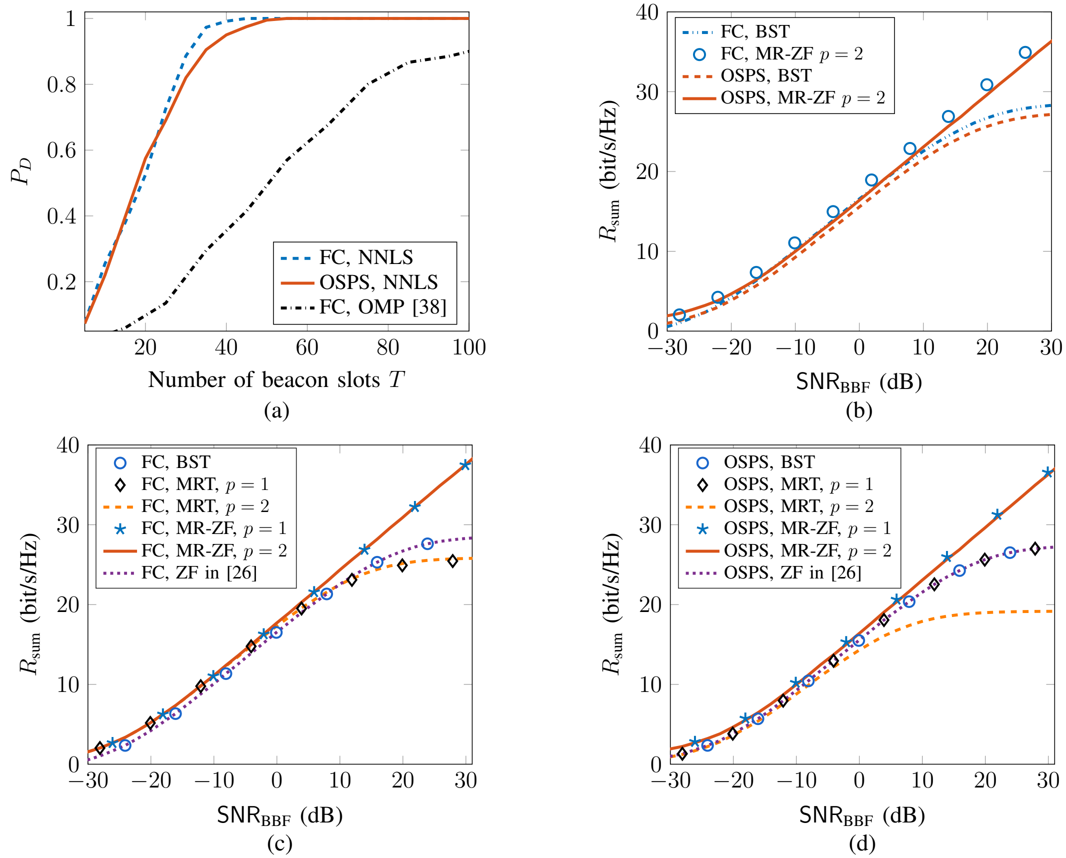



Fig. 7: The simulations based on QuaDRiGa: (a) The initial BA detection probability vs. the training overhead, with $\text{SNR}_{\text{BBF}} = -15$ dB. (b) The sum spectral efficiency of different transmitter architectures vs. increasing $\text{SNR}_{\text{BBF}}$. (c) The sum spectral efficiency of the FC architecture vs. increasing $\text{SNR}_{\text{BBF}}$. (d) The sum spectral efficiency of the OSPS architecture vs. increasing $\text{SNR}_{\text{BBF}}$.

# Some references on our work

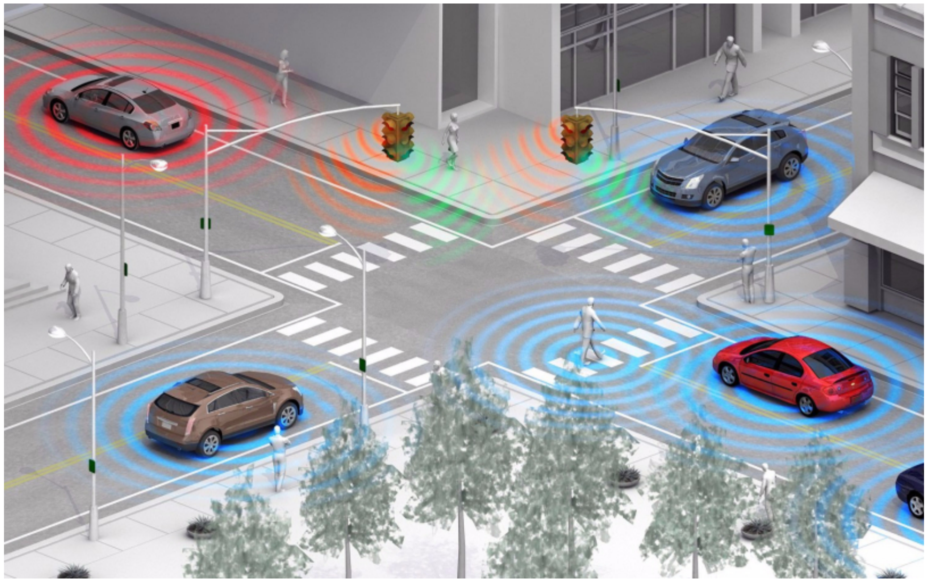
- X. Song, S. Haghighatshoar, and G. Caire, “A scalable and statistically robust beam alignment technique for mm-wave systems.” *IEEE Trans. on Wireless Comm.*, May 2018.

- X. Song, S. Haghighatshoar, and G. Caire, “Efficient Beam Alignment for Millimeter Wave Single-Carrier Systems With Hybrid MIMO Transceivers,” *IEEE Trans. on Wireless Comm.* March 2019.

- Xiaoshen Song, Thomas Kühne, and G. Caire, “Fully/Partially-Connected Hybrid Beamforming Architectures for mmWave MU-MIMO,” *IEEE Trans. on Wireless Comm.* 2020.

# Joint Radar & Communication

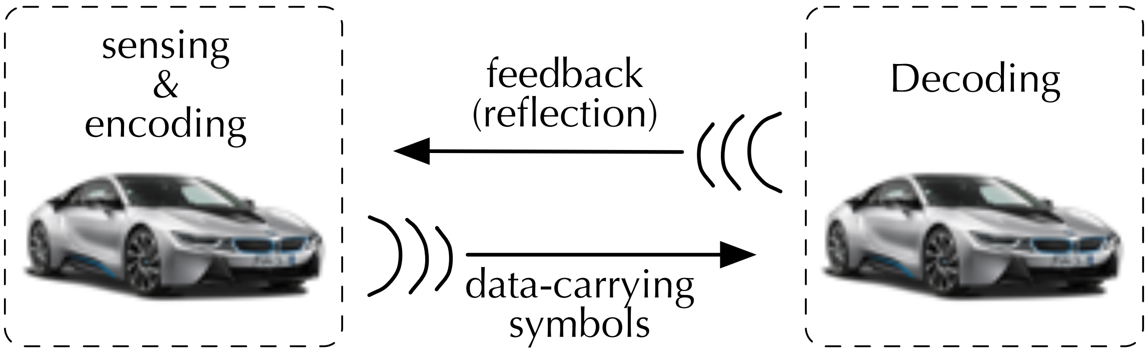




- Future networks must support exponentially increasing data traffic, while ensuring new mobility services such as V2X.
- Limitations of current technologies (e.g. CoMP, massive MIMO, PS) relying on full channel knowledge and static network models.
- A key-enabler is the ability to continuously sense dynamically changing "state", and react accordingly by exchanging information.

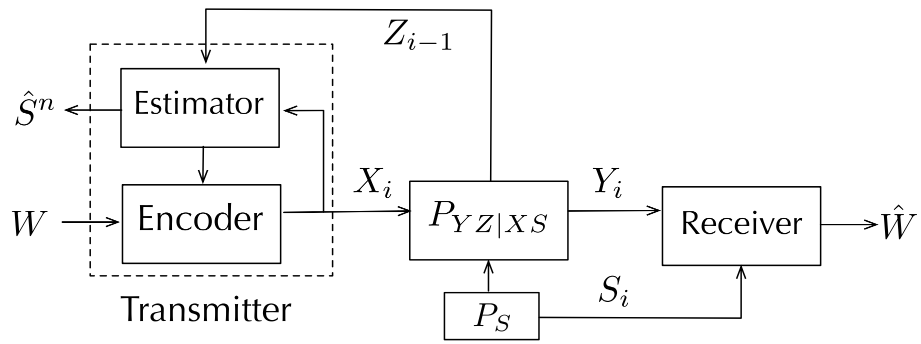
# Motivation: JRC for V2V and V2X






- The spectrum crunch encourages to use the same frequency bands for both functions (e.g. IEEE S band shared between LTE and radar).
- One vehicle wishes to track the "state" (velocity, range) and simultaneously convey a message (safety/traffic-related).

# Information-Theoretic Toy Model




- Transmitter sends a message $W$ and estimates a state sequence $S^n$ via "generalized feedback": strictly causal channel output $Z_{i-1}$.
- Receiver decodes $\hat{W}$ from its observation $Y^n$ and $S^n$ (known perfectly).
- A memoryless state-dependent channel:

$$P_{WX^nS^nY^nZ^n}(w, \mathbf{x}, \mathbf{s}, \mathbf{y}, \mathbf{z}) = P(w) \prod_{i=1}^{n} P_S(s_i) \prod_{i=1}^{n} P(x_i|wz^{i-1}) P_{YZ|XS}(y_i z_i|x_i s_i).$$

# Information-Theoretic Toy Model

- A $(2^{nR}, n)$ code consists of a message set, an encoder, a decoder, and a state estimator.
- The state estimate is measured by the expected distortion

$$\mathbb{E}[d(S^n, \hat{S}^n)] = \frac{1}{n}\sum_{i=1}^{n}\mathbb{E}[d(S_i, \hat{S}_i)]$$

- A rate distortion pair $(R, D)$ is achievable if

$$\lim_{n\to\infty} P(\hat{W} \neq W) = 0$$

and

$$\limsup_{n\to\infty} \mathbb{E}[d(S^n, \hat{S}^n)] \leq D.$$

- The capacity-distortion tradeoff $C(D)$ is the supremum of $R$ such that $(R, D)$ is achievable.

# Fundamental Limit

**Theorem**

*The capacity-distortion tradeoff of the state-dependent memoryless channel with the i.i.d. states is given by*

$$C(D) = \max I(X;Y|S)$$

*where the maximum is over all $P_X$ satisfying $\mathbb{E}[d(S,\hat{S})] \leq D$ and the joint distribution of $SXYZ\hat{S}$ is given by*

$$P_X(x)P_S(s)P_{YZ|XS}(yz|xs)P_{\hat{S}|XZ}(\hat{s}|xz).$$

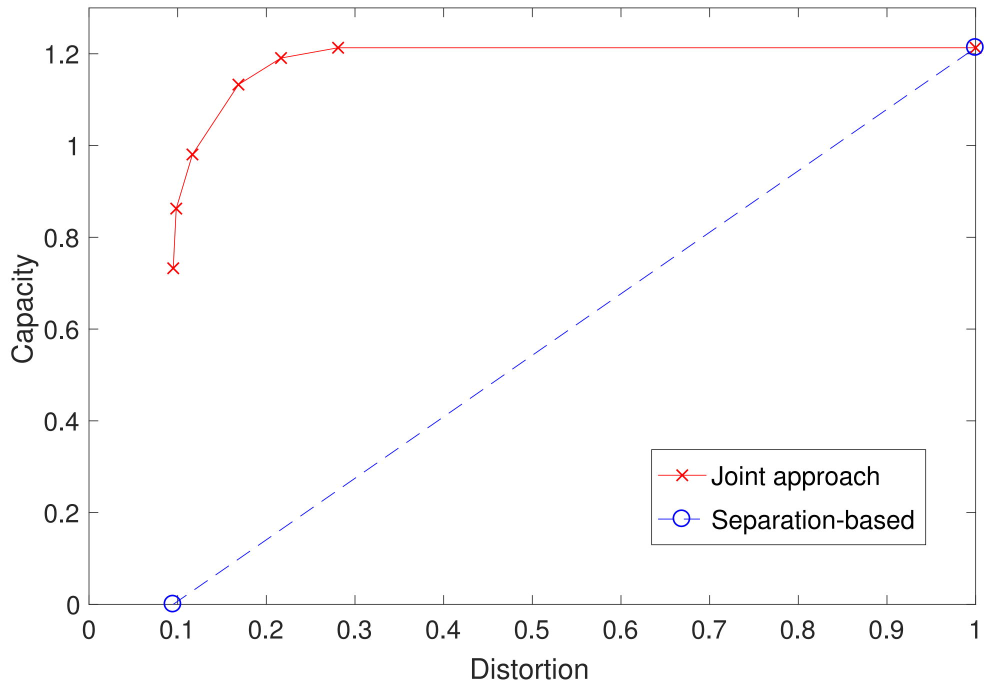
- Achievability builds on random encoding and jointly typicality decoding.
- We can use a deterministic estimator

$$\hat{s} = \hat{s}(x,z) = \arg\min_{s' \in \mathcal{S}} \sum_{s \in \mathcal{S}} P_{S|XZ}(s|x,z)d(s,s')$$

# A Gaussian AWGN Example

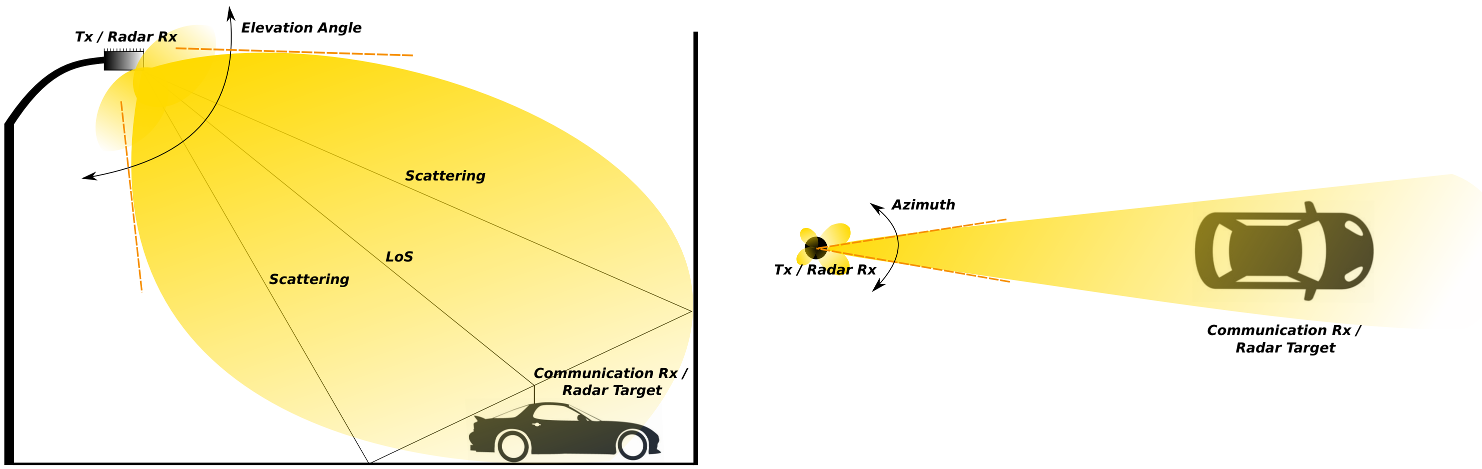
- A real fading channel $Y_i = S_i X_i + N_i$ where
  - $S_i, N_i$ are i.i.d. Gaussian distributed with zero mean and unit variance
  - $\{X_i\}$ satisfies the average power constraint $\frac{1}{n}\sum_i \mathbb{E}[|X_i|^2] \leq P$.
- Quadratic distortion function: the expected distortion is $\mathbb{E}\left[\frac{1}{1+|X|^2}\right]$.
- Two extreme points:
  - $D_{\min}$ achieved by $2$-ary pulse amplitude modulation (PAM).
  - $C_{\max} = \mathbb{E}[\log(1+|S|^2 P)]$ achieved by Gaussian input.

## $C(D)$ of Gaussian channel with $P = 10$ dB




- A significant gain with respect to resource-sharing.
- Feedback is useful only for state sensing.

# A Practical Scenario




- Radar periodically scanning an angular sector (e.g., using a phased array)
  - One target in each sector
  - No need to perform DOA estimation
  - Possibility to have multi-path scattering components: LoS, ground reflection, buildings and metal surfaces reflections, etc.

# SISO Channel Model

## Time-Frequency Selective Channel

- Radar channel

$$h(t,\tau) = \sum_{p=0}^{P-1} h_p \delta(\tau - \tau_p) e^{j2\pi\nu_p t}$$

- Radar received signal without noise

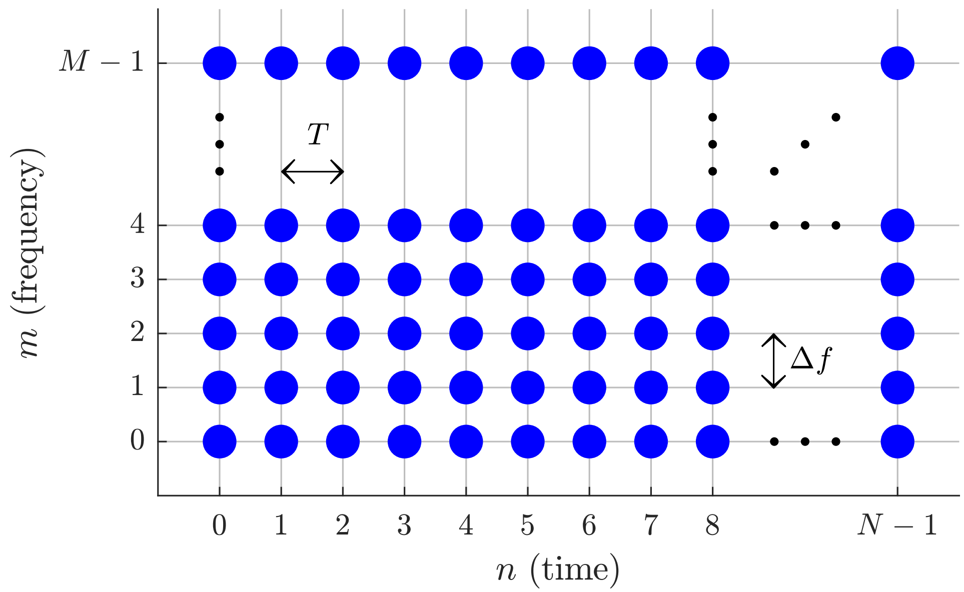
$$y(t) = \int h(t,\tau) s(t-\tau) d\tau = \sum_{p=0}^{P-1} h_p s(t-\tau_p) e^{j2\pi\nu_p t}$$

- Communication channel

$$h_{\text{com}}(t,\tau) = \sum_{p=0}^{P-1} g_p e^{j\pi\nu_p t} \delta\left(\tau - \frac{\tau_p}{2}\right)$$

# Modulation on a Time-Frequency Grid

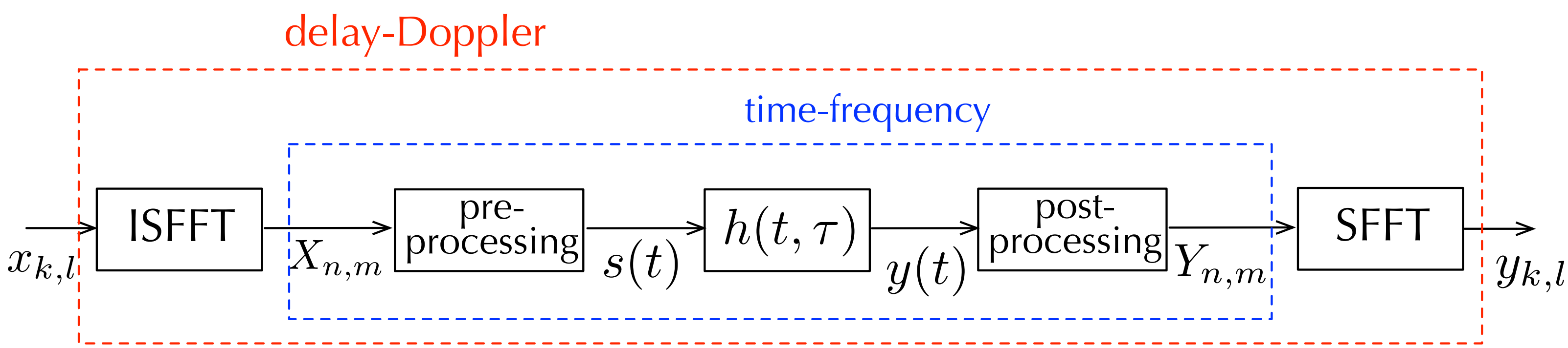
## Transmission using $M$ subcarriers and $N$ time slots




- Total bandwidth is divided in $M$ subcarriers, i.e. $B = M\Delta f$.
- $T = \frac{1}{\Delta f}$ is one symbol duration, $T_{\text{frame}} = NT$.
- $\{x_{n,m}\}$ satisfies average power constraint $\mathbb{E}[|x_{n,m}|^2] \leq P$.
- The parameters are chosen such that

$$\nu_{\max} < \Delta f \,, \quad \tau_{\max} < T$$

# OFDM and OTFS




- Cyclic prefix OFDM uses Inverse DFT/DFT in time-frequency domain.
- OFTS is a modulation patented by Cohere [13] using the Zak transform[14].
- Mapping from delay-Doppler to time-frequency domains (ISFFT):

$$X[n,m] = \frac{1}{\sqrt{NM}} \sum_{k=0}^{N-1} \sum_{l=0}^{M-1} x_{k,l} e^{j2\pi\left(\frac{nk}{N} - \frac{ml}{M}\right)}$$

# Some Details of OTFS

- Pre-processing:

$$s(t) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} X[n,m] \, g_{\text{tx}}(t - nT) \, e^{j2\pi m \Delta f (t-nT)}$$

- Post-processing: filter and sampling at $t = nT, f = m\Delta f$.

$$Y(t,f) = C_{r,g_{\text{rx}}}(t,f) = \int y(t') \, g_{\text{rx}}^{*}(t' - t) \, e^{-j2\pi f t'} dt'$$

- After SFFT, the output of dimension $NM$ in delay-Doppler domain :

$$\mathbf{y} = \sum_{p=0}^{P-1} h_p \boldsymbol{\Psi}^p(\tau_p, \nu_p)\mathbf{x} + \boldsymbol{w}$$

This holds for any transmit/receive pulse pair.

# ML Joint Parameter Estimation

- Let $\boldsymbol{\theta} = (\boldsymbol{\tau}, \boldsymbol{\nu}, \mathbf{h})$ a vector to be estimated.
- Rearranging terms, the log-likelihood function is given by

$$l(\mathbf{y}|\boldsymbol{\theta}, \mathbf{x}) = \sum_p \underbrace{\frac{|\mathbf{x}^{\mathsf{H}} \boldsymbol{\Phi}_p^{\mathsf{H}} \mathbf{y}|^2}{\mathbf{x}^{\mathsf{H}} \boldsymbol{\Phi}_p^{\mathsf{H}} \boldsymbol{\Phi}_p \mathbf{x}}}_{S_p(\tau_p, \nu_p)} - \sum_p \underbrace{\frac{\mathbf{x}^{\mathsf{H}} \boldsymbol{\Phi}_p^{\mathsf{H}} \left( \sum_{q \neq p} h_q \boldsymbol{\Phi}_q \right) \mathbf{x} \mathbf{y}^{\mathsf{H}} \boldsymbol{\Phi}_p \mathbf{x}}{\mathbf{x}^{\mathsf{H}} \boldsymbol{\Phi}_p^{\mathsf{H}} \boldsymbol{\Phi}_p \mathbf{x}}}_{I_p(\{h_q\}_{q \neq p}, \boldsymbol{\tau}, \boldsymbol{\nu})}$$

- Initialization: $n = 0$

  for each $p$, find $(\hat{\tau}_p, \hat{\nu}_p)$ maximizing $S_p$.
- Iterations: $n = 1, \ldots,$

  for each $p$, update $(\hat{\tau}_p(n), \hat{\nu}_p(n))$ by treating all others fixed

$$(\hat{\tau}_p(n), \hat{\nu}_p(n)) = \text{arg} \max_{(\tau_p, \nu_p) \in \Gamma} S_p(\tau_p, \nu_p) - I_p(\tau_p, \nu_p, \{\hat{h}_q, \hat{\tau}_q, \hat{\nu}_q\}_{q \neq p}^{(n-1)})$$

# Crame-Rao Lower Bound

- 4P unknown parameters to estimate from $NM$ noisy samples.

$$\boldsymbol{\theta} = \left( \left| \mathbf{h} \right|, \angle \mathbf{h}, \boldsymbol{\tau}, \boldsymbol{\nu} \right)$$

- CRLB can be derived by computing the $4P \times 4P$ Fischer information matrix with a special structure (each block matrix of $P \times P$ is diagonal).

$$[\mathbf{I}(\boldsymbol{\theta}, \mathbf{x})]_{i,j} = 2 P_{\text{avg}} \text{Re} \left\{ \sum_{k,l} \left[ \frac{\partial s_p[k,l]}{\partial \theta_i} \right]^* \left[ \frac{\partial s_{n,m}}{\partial \theta_j} \right] \right\},$$

where

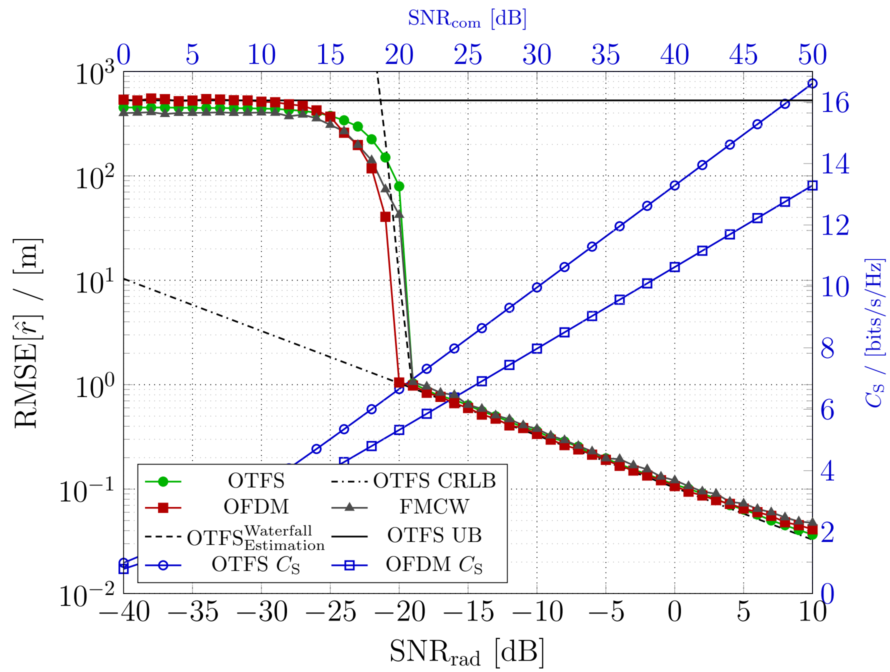
$$s_p[k,l] = \left| h_p \right| e^{j \angle h_p} \sum_{k'=0}^{N-1} \sum_{l'=0}^{M-1} \boldsymbol{\Psi}_{n,k'}^{p} \left[ l, l' \right] x_{k',m} \,,$$

# 802.11p-like Parameters

| IEEE 802.11p[17] | |
|---|---|
| $f_c = 5.89$ GHz | $M = 64$ |
| $B = 10$ MHz | $N = 50$ |
| $\Delta f = B/M = 156.25$ kHz | $T_{\rm cp} = \frac{1}{4}T = 1.6\,\mu$s |
| $T = 1/\Delta f = 6.4\,\mu s$ | $T_{\rm o} = T_{\rm cp} + T = 8\,\mu$s |
| $r_{\max}^{\rm otfs} < Tc/2 \simeq 960$ m | $r_{\max}^{\rm ofdm} < T_{\rm cp}c/2 \simeq 240$ m |
| $\sigma_{\rm rcs} = 1$ m$^2$ | $G = 100$ |
| $r = 20$ m | $v = 80$ km/h |

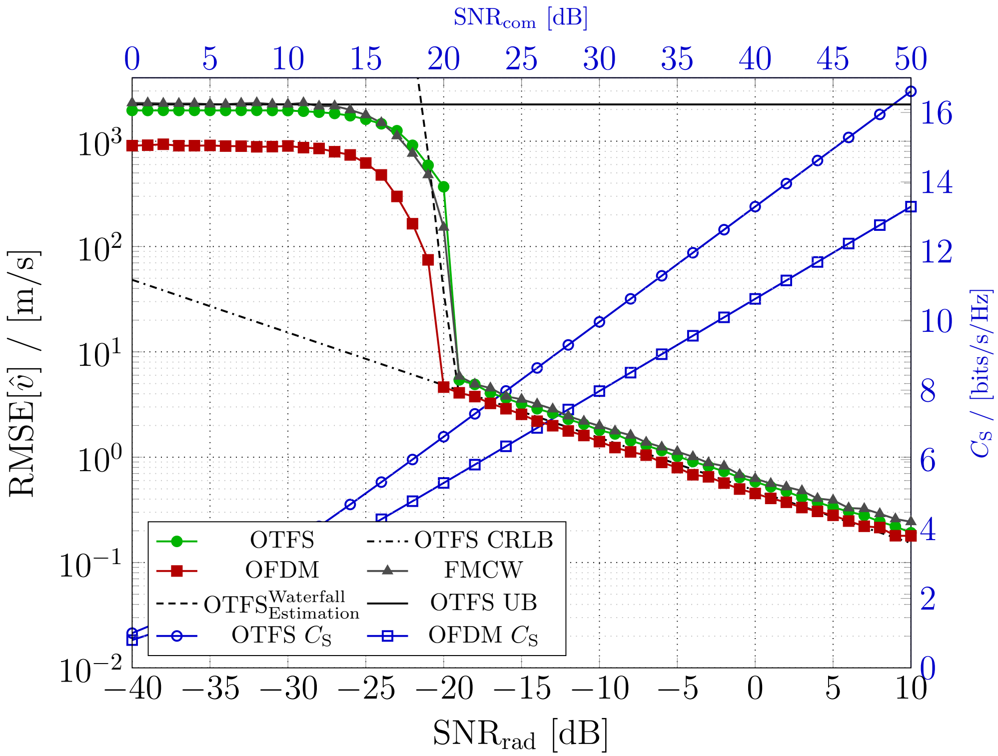
[17] D. H. Nguyen and R. W. Heath, "Delay and Doppler processing for multi-target detection with IEEE 802.11 OFDM signaling", ICASSP 2017

# Range Estimation and Achievable Rates

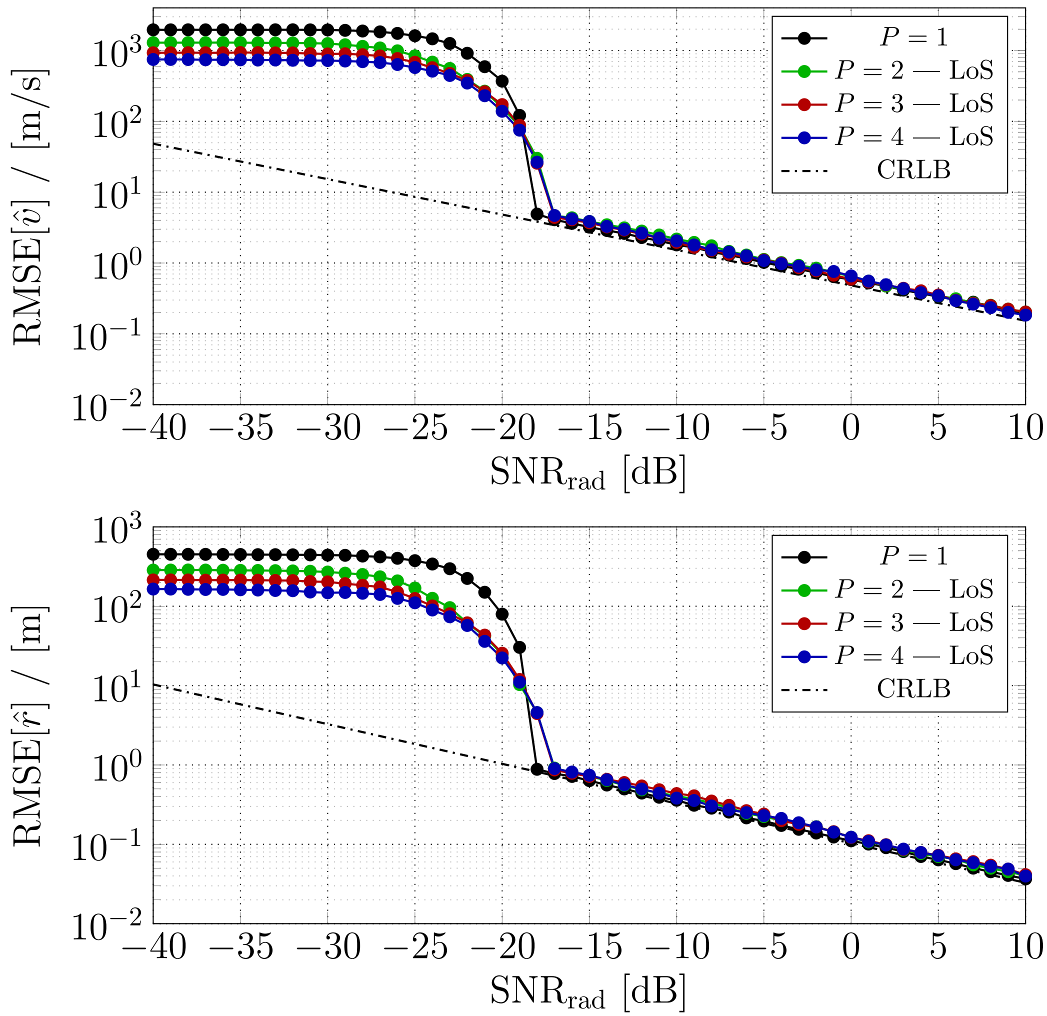



- Under a simplified scenario, OFDM/OTFS can yield a significant data rate without compromising radar estimation.

# Velocity Estimation



# Presence of Multipath




- The proposed scheme works well for a multi-path channel too.

# If You Are Interested ...



## Tutorial at ICASSP, May 4, 2020, Barcelona

- Title: "Information Extraction in Joint Millimeter-Wave State Sensing and Communications: Fundamentals to Applications"
- Speakers: Kumar Vijay Mishra (US Army Research Laboratory), Bhavani Shankar (University of Luxembourg), and Mari Kobayashi
- Details are available on https://2020.ieeeicassp.org/program/tutorials/

# Conclusions and On-Going Work

- Fast and scalable initial beam acquisition with large arrays at both BS and UE is possible using “second-order statistics” (quadratic measurements).

- After BA, the mmWave channel becomes *almost* a single delay and Doppler shift, with good SNR: easily handle with single-carrier modulation and standard synchronization schemes.

- For a MU-MIMO BS at mmWaves, the OSPS architecture (with BB precoding) yields a very attractive tradeoff between performance and complexity.

- To Do: efficient beam tracking algorithms (after initial BA).

# Conclusions and On-Going Work

- Joint Radar parameter estimation and communication is very attractive: optimal estimation at no cost for data rate.

- OTSF yields complex receivers, but it is more spectrally efficient than OFDM and more robust to high Doppler.

- To Do: Radar-aided initial BA, and/or communication-aided Radar detection: Can joint operations benefit both functions?

# Thank You