

Estimating Millimeter Wave Channels Using Out-of-Band Measurements

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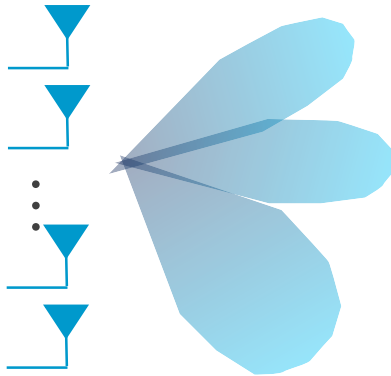
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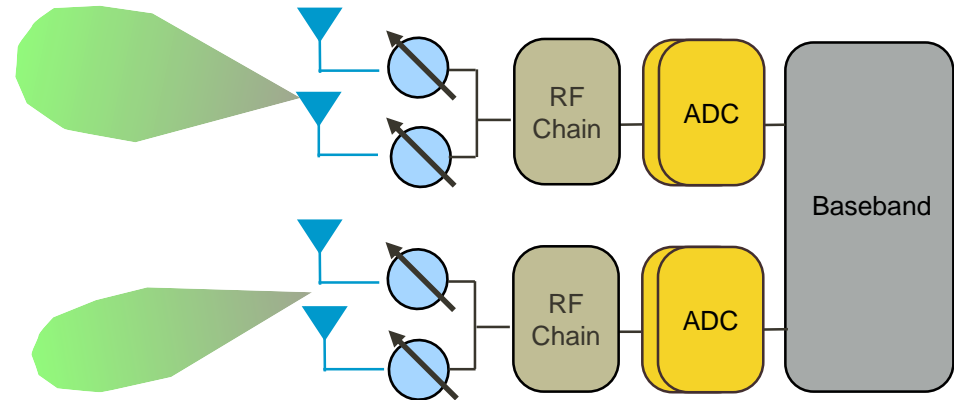
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Millimeter wave wireless communication

Many antennas at
the TX and RX



Hardware constraints impact
how the antennas are used



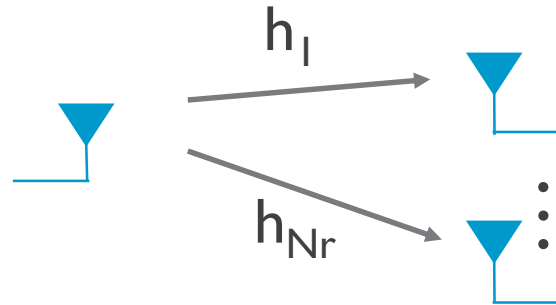
MmWave is finding applications to 5G, WLAN, and connected cars

Challenge of channel estimation in mmWave

Conventional SIMO

Send N_{tr} training

train



Estimate all coefficients at the same time

SIMO w/ analog beamforming

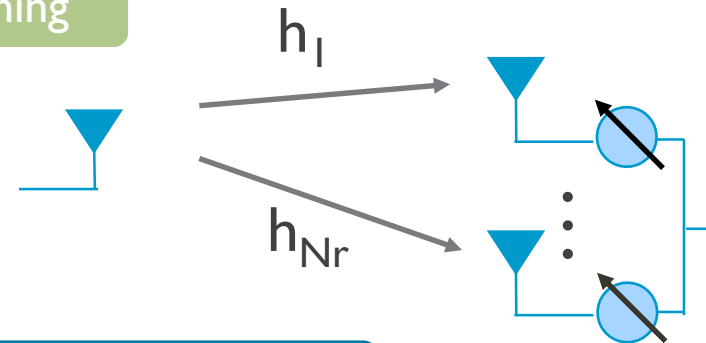
Send $N_r N_{tr}$ training

train

train

...

train

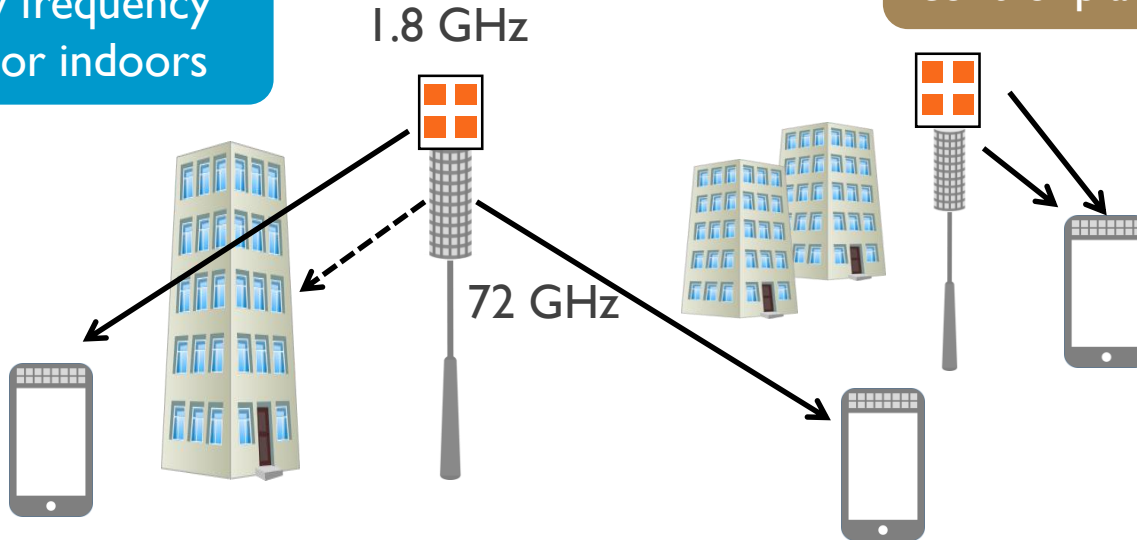


Estimate each coefficient separately (sparsity can reduce measurements)

SNR is low at mmWave $\implies N_{tr}$ is big

Multiband operation for mmWave

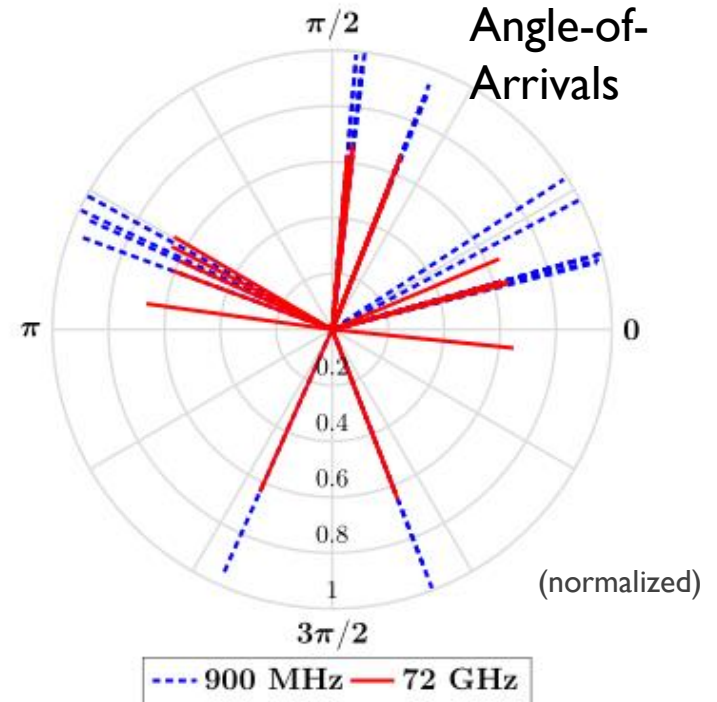
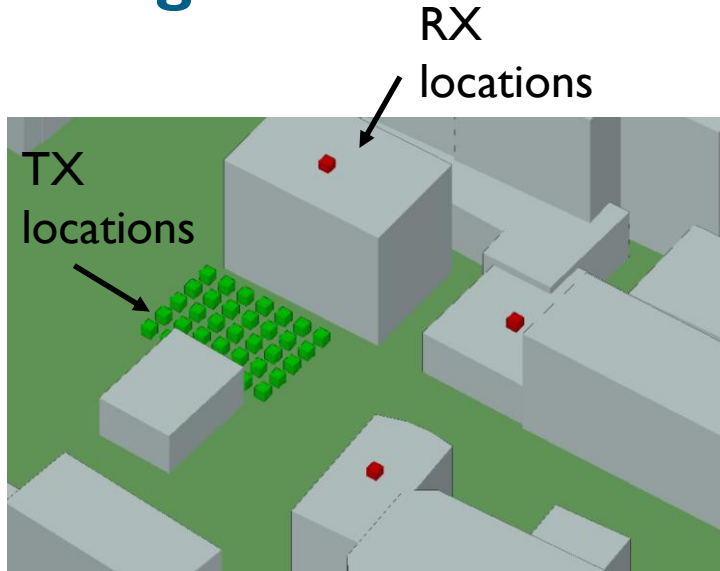
Fallback to low frequency
when blocked or indoors



Use low frequency for
control plane, high for data

What can be exploited from the sub 6 GHz channel
measurements to improve mmWave channel estimation?

What might be similar?

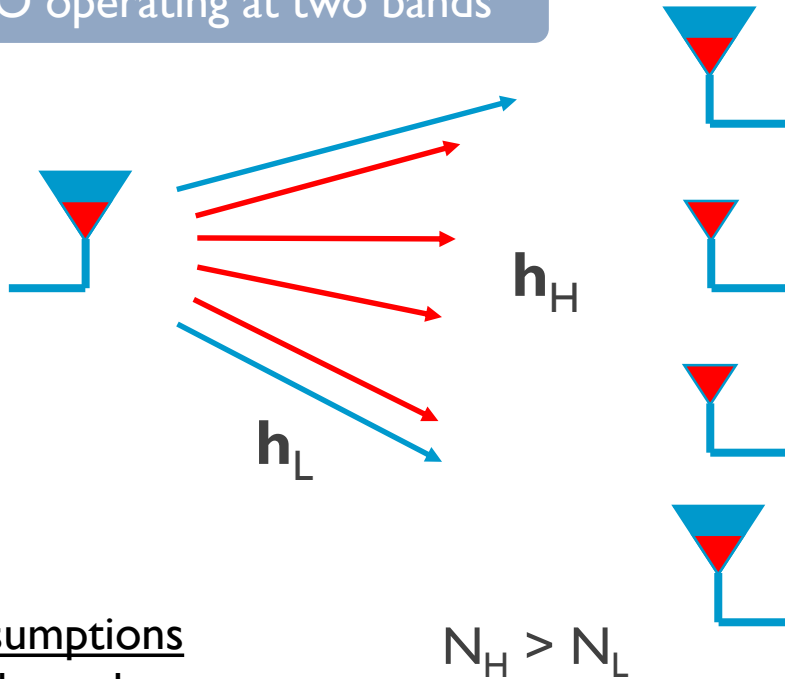


MmWave has higher spatial resolution (antennas) and temporal resolution (bandwidth)

Substantial spatial congruence though not complete

Problem setup

SIMO operating at two bands



Main assumptions

NLOS channels

Narrowband

Neglect hardware constraints

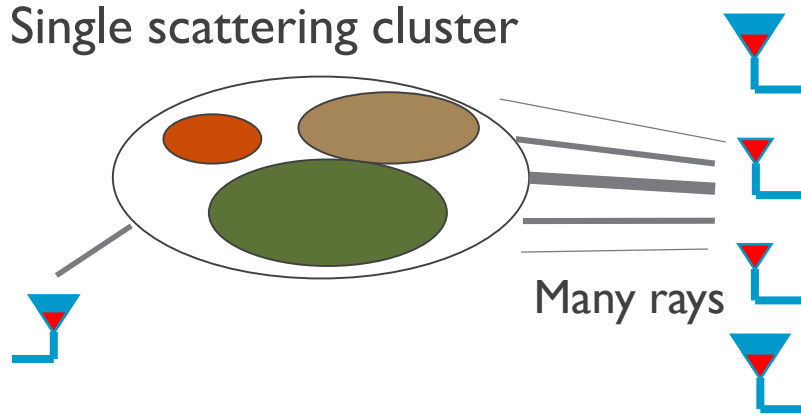
Compute low frequency spatial correlation matrix

$$\mathbf{R}_L = \mathbb{E} [\mathbf{h}_L \mathbf{h}_L^*]$$

Construct an estimate of the high frequency spatial correlation matrix

$$\hat{\mathbf{R}}_H = f(\mathbf{R}_L)$$

Modeling spatial correlation



Assuming small angle spread, ULA

Wavelength dependence

$$[\mathbf{R}]_{i,j} = e^{j(i-j)2\pi \frac{d}{\lambda} \sin(\bar{\theta})} B \left((i-j)2\pi \frac{d}{\lambda} \sin(\bar{\theta}) \sigma_{\theta} \right)$$

Antenna element
difference

Char. Fun. of normalized
AoA distribution

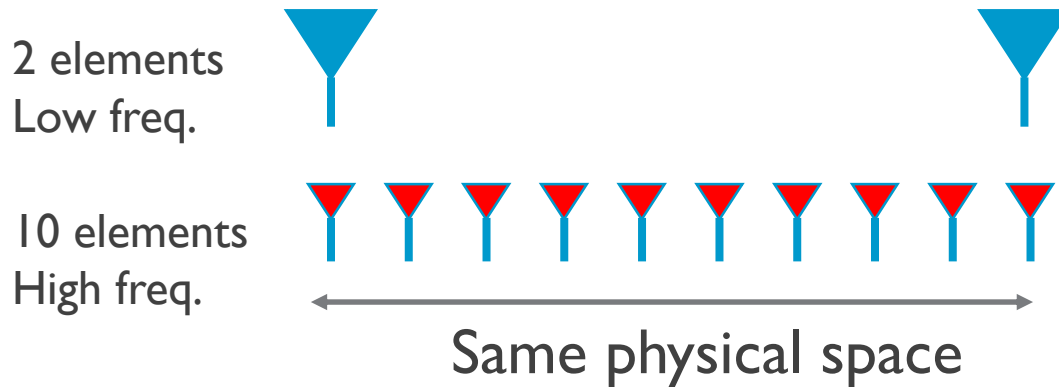
Mean AoA $\bar{\theta}$
Angle spread σ_{θ} (varies w/ frequency)
Given AoA distribution

Correlation transform

Common approach used with FDD reciprocity w/ small H-L

$$\mathbf{T}^* \mathbf{R}_L \mathbf{T} = \mathbf{R}_H$$

Square transformation matrix in conventional work



Different dimensions

Sample **larger portion** of the angle spread function

$$\frac{d}{\lambda_L} = \frac{1}{2}$$

$$\frac{d}{\lambda_H} = \frac{1}{2}$$

$$9 \frac{d}{\lambda_H} = 9 \frac{1}{2}$$

$$\max(i - j) = 9$$

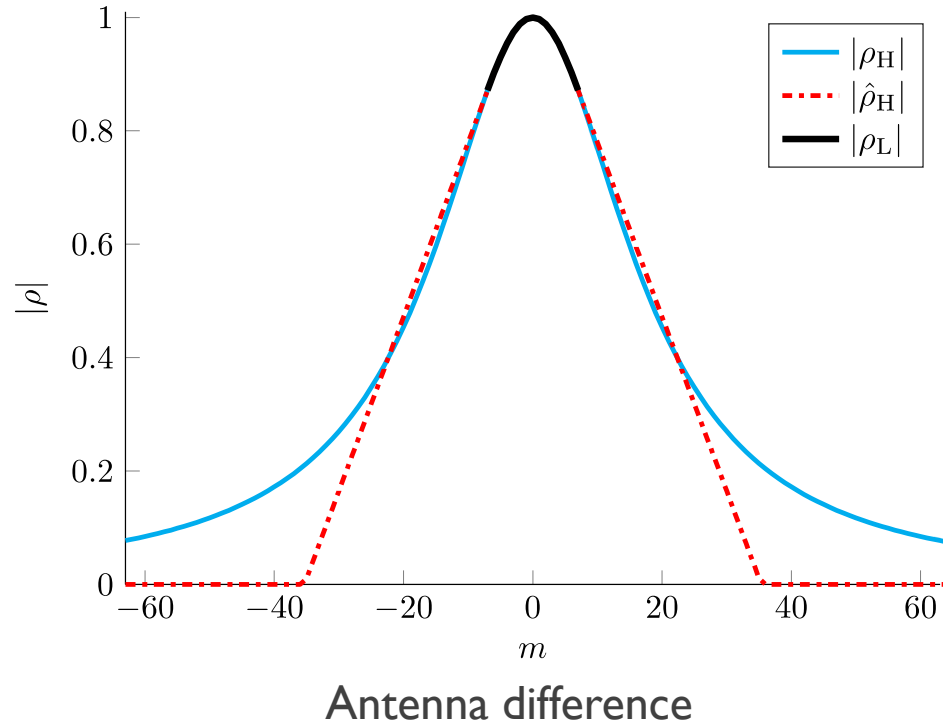
Proposed solutions

Approach #1

Interpolation and extrapolation of the transformed spatial correlation matrix (more general but less accurate)

Approach #2

Parametric estimation of the mean AoA and angle spread (requires knowledge of distribution)



Evaluating performance of a MMSE estimator

Assume that the estimated covariance is used for MMSE estimation

Theorem 1. *If the true correlation matrix, \mathbf{R}_H , and the translated correlation matrix, $\hat{\mathbf{R}}_H$, differ by an additive perturbation $\mathbf{\Gamma}$ (i.e., $\hat{\mathbf{R}}_H = \mathbf{R}_H + \mathbf{\Gamma}$) that ensures positive definiteness of $\hat{\mathbf{R}}_H$, then the EMSE of the estimator is*

$$\text{EMSE} = \text{tr}(\mathbf{\Upsilon} \mathbf{R}_{\tilde{\mathbf{y}},H} \mathbf{\Upsilon}^*), \quad (12)$$

where $\mathbf{R}_{\tilde{\mathbf{y}},H} = \mathbb{E}[\tilde{\mathbf{y}}\tilde{\mathbf{y}}^*] = (\tilde{\mathbf{S}}\mathbf{R}_H\tilde{\mathbf{S}}^* + \sigma_v^2\mathbf{I}_{KM})$ and

$$\begin{aligned} \mathbf{\Upsilon} = & \mathbf{\Gamma}\tilde{\mathbf{S}}^*(\mathbf{R}_{\tilde{\mathbf{y}},H} + \tilde{\mathbf{S}}\mathbf{\Gamma}\tilde{\mathbf{S}}^*)^{-1} \\ & - \mathbf{R}_H\tilde{\mathbf{S}}^*\mathbf{R}_{\tilde{\mathbf{y}},H}^{-1}\tilde{\mathbf{S}}(\mathbf{I}_M + \mathbf{\Gamma}\tilde{\mathbf{S}}^*\mathbf{R}_{\tilde{\mathbf{y}},H}^{-1}\tilde{\mathbf{S}})^{-1}\mathbf{\Gamma}\tilde{\mathbf{S}}^*\mathbf{R}_{\tilde{\mathbf{y}},H}^{-1}. \end{aligned} \quad (13)$$

MSE from true cov.



$$\text{MSE} = \text{MMSE} + \text{EMSE}$$



Excess mean squared error

Simulation setup

Low frequency system

$$\bar{\theta} = 45^\circ \quad \sigma_\theta = 15^\circ \quad \text{Truncated Laplacian AoA}$$

900 MHz with 4 antennas

High frequency system

Keep $\frac{d}{\lambda}$ constant, vary the number of antennas

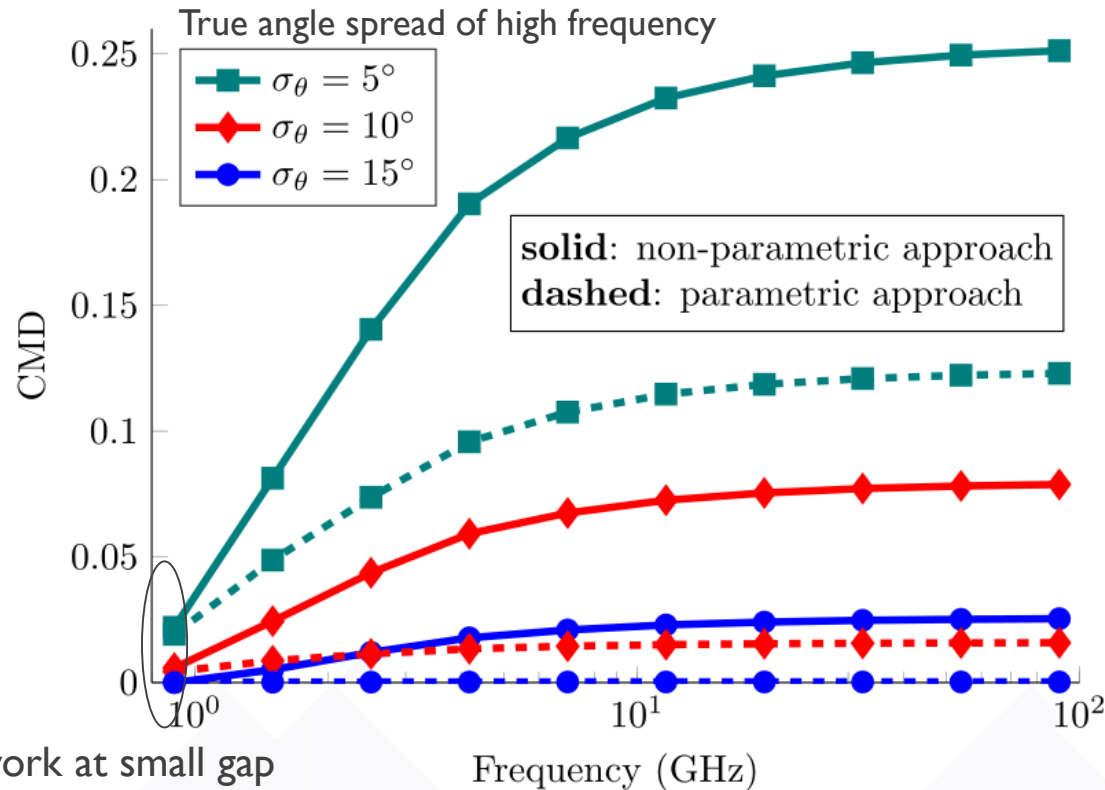
Vary true angle spread (model mismatch)

Correlation distance

$$d_{\text{corr}}(\mathbf{R}_H, \hat{\mathbf{R}}_H) = 1 - \frac{\text{tr}(\mathbf{R}_H \hat{\mathbf{R}}_H)}{\|\mathbf{R}_H\|_F \|\hat{\mathbf{R}}_H\|_F} \in (0, 1]$$

Model mismatch
hurts both
approaches

Parametric has
better performance
when model is good

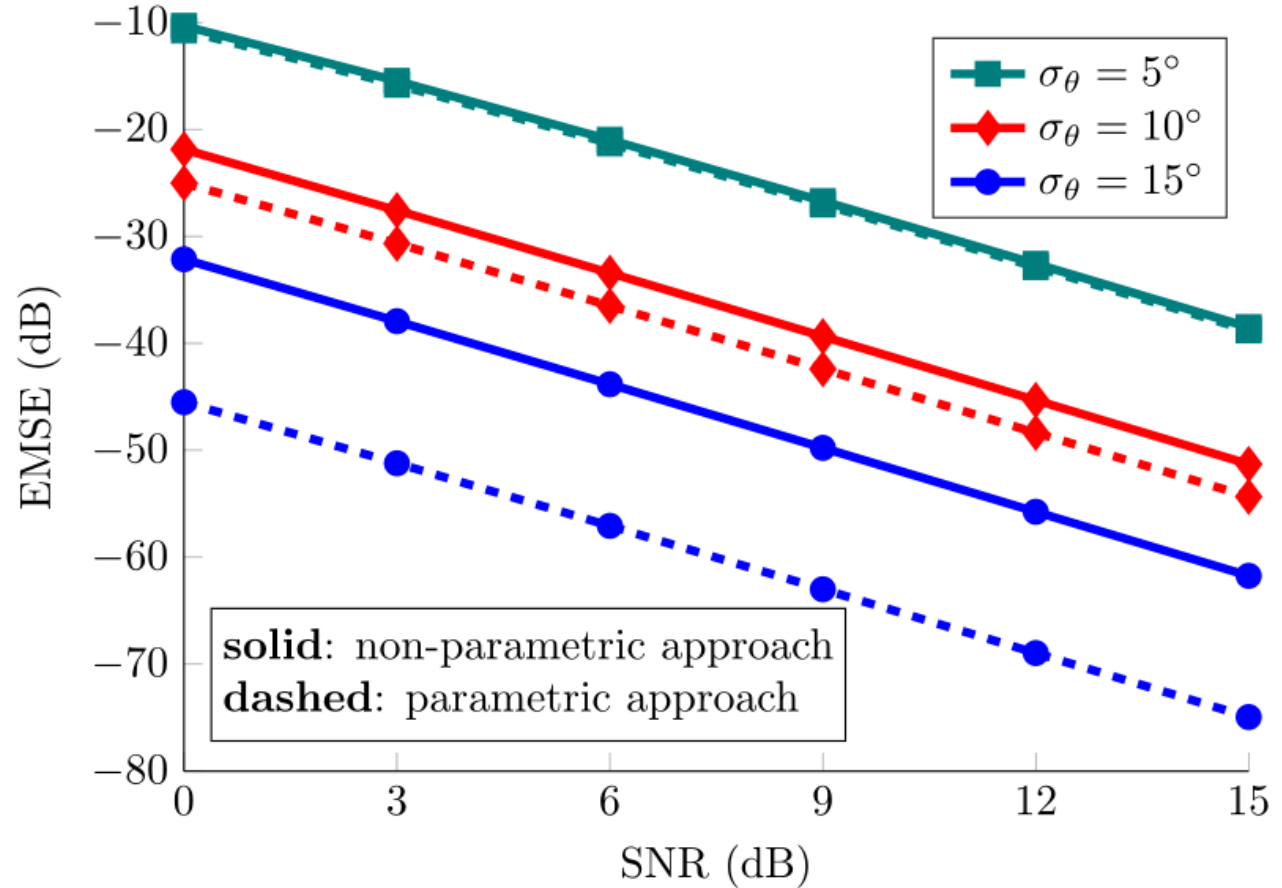


Excess MSE

-sub 6-GHz
frequency 900
MHz -4 antennas
-mmWave
frequency 30 GHz
- 32 antennas

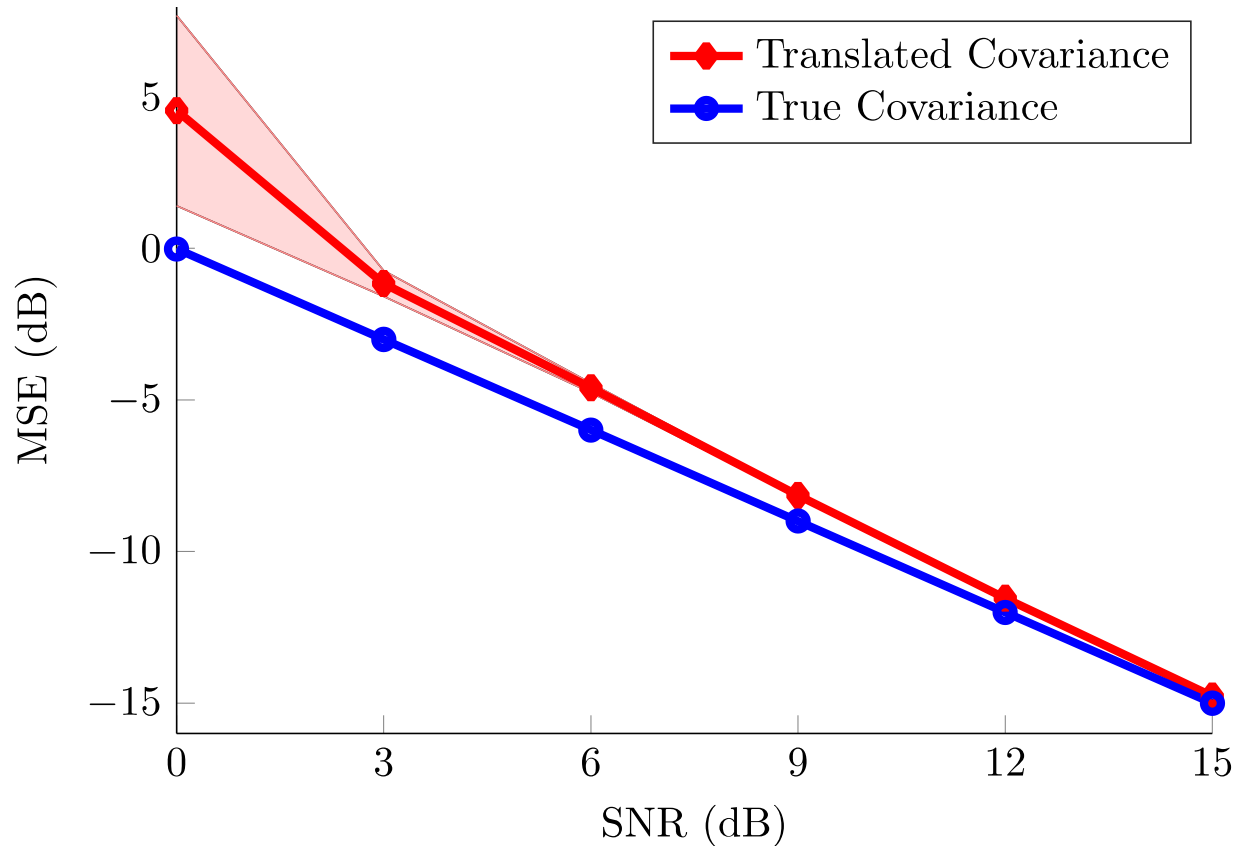
Error increases
with angle spread
mismatch

Decreases with
SNR



Mean squared error comparison

Performance better at higher SNR, but low SNR is more important for mmWave



Conclusions

It may be possible to exploit some lower frequency channel information for higher frequencies channel estimation

Going beyond the simple setup: other array geometries, more complicated channels, channel mismatch, broadband channels, MIMO, hardware constraints

Making better use of the spatial correlation information: compressed channel estimation, compressive covariance estimation, initialization for beam training