Signal processing at the mm wave frontier

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ICB

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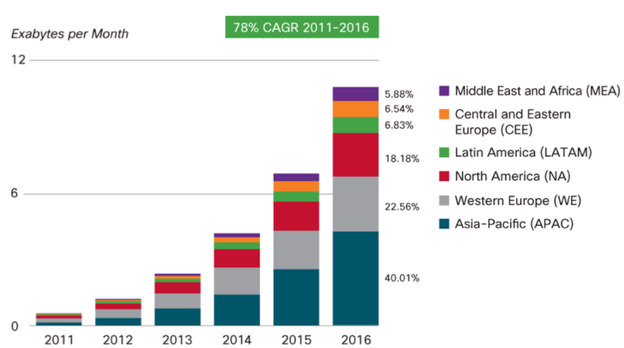
Why the buzz?

- “Unlimited” spectrum
  - 30-300 GHz (with strict defn of 10-1 mm wavelength)
  - 60 GHz has received the most recent attention (unlicensed)
  - 71-76 and 81-86 GHz for semi-unlicensed point-to-point
  - 100+ GHz: the wild west of wireless
- Why now?
  - Because we can (mass market RFICs now feasible)
  - Smart phone induced capacity crisis
  - Fits with logic of continued WiFi growth

Figure 2. Global Mobile Data Traffic Forecast by Region



Source: Cisco VNI Mobile, 2012

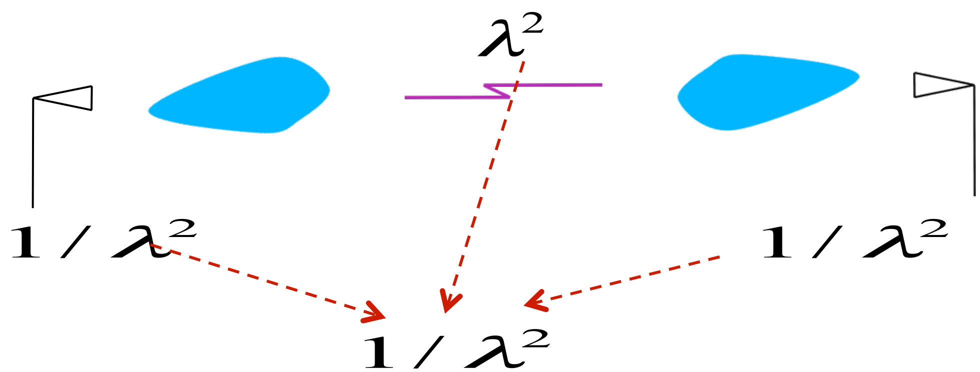
Agenda today

- How not to fight physics
  - How tiny wavelengths impact us
  - What applications are a natural fit to mm wave
- Case study: from application to theory and back
  - Xtreme spatial reuse via 1000 elt antennas ➔ new theory of compressive estimation
  - Algorithms for attaining CRB
  - Tracking users for mm wave to the mobile
- Challenges and opportunities
  - New MIMO architectures
  - Very high bandwidths

Message: Beyond the hype lie significant intellectual opportunities

How not to fight physics

High directionality is essential



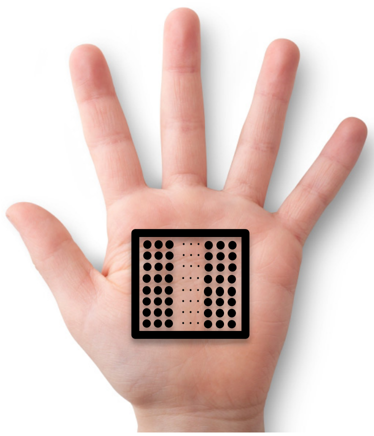
Friis formula for free space propagation

$$P_{RX} = P_{TX}\, G_{TX}\, G_{RX} \frac{\lambda^2}{16\pi^2 R^2}\,, \quad \text{in terms of antenna gains}$$

$$P_{RX} = P_{TX} \frac{A_{TX} A_{RX}}{\lambda^2 R^2}\,, \quad \text{in terms of antenna apertures}$$

Highly directional antennas critical for adequate link budget
High directionality attainable with reasonable form factor

High directionality is attainable

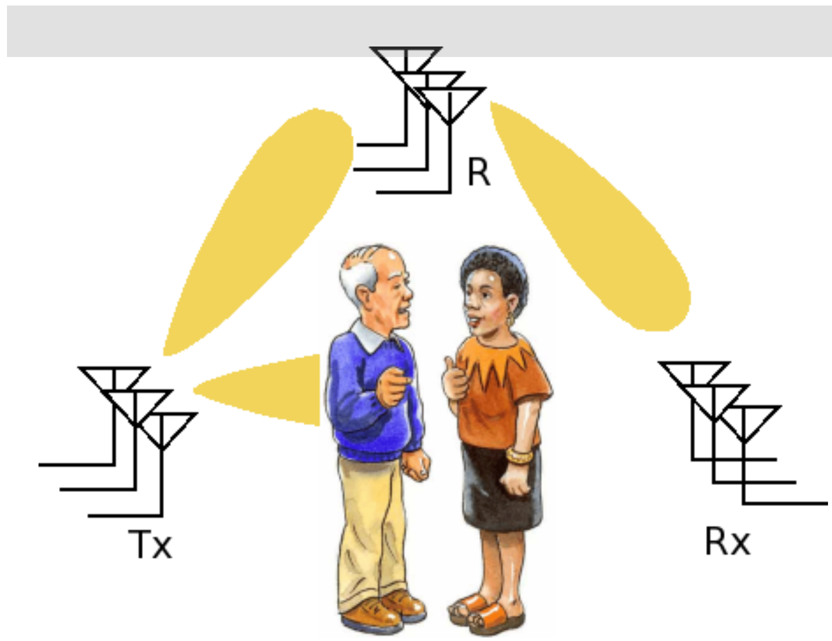


Massive MIMO in your palm
32 x 32 element array fits within 8cm x 8cm
Electrically large, physically small

But how would we steer such large arrays?

Electronic steerability is essential

Relay or reflector



Objects look bigger at smaller wavelengths (Huygen's principle)
➔Cannot burn through or diffract around obstacles
➔Must steer around them

Again, how do we steer large arrays?

Oxygen absorption and rain can be scary

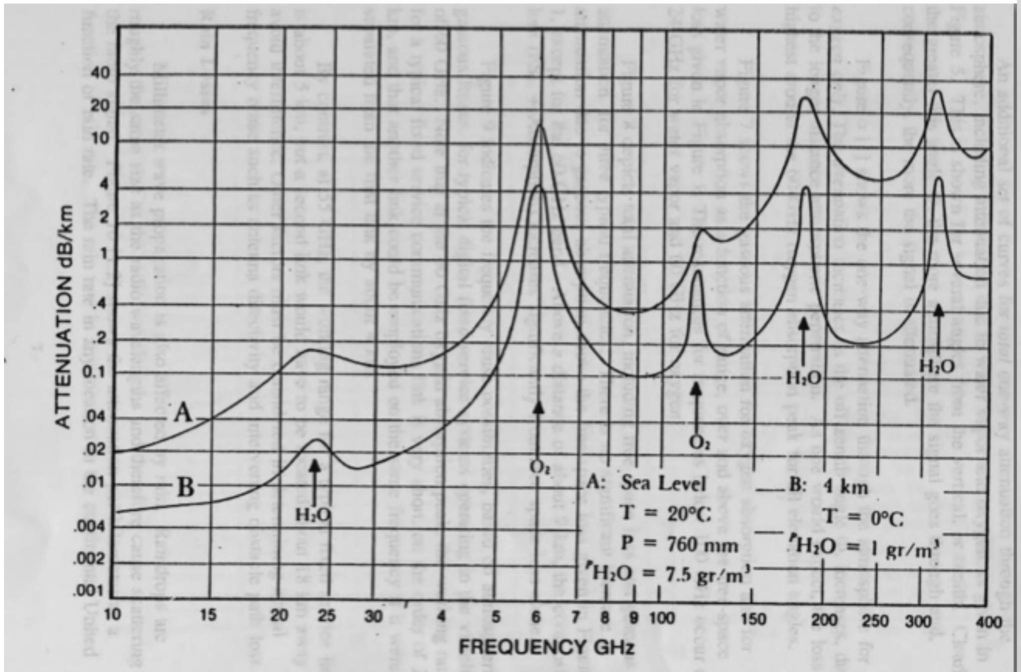


Figure 4: **Average Atmospheric Absorption of Millimeter Waves.**

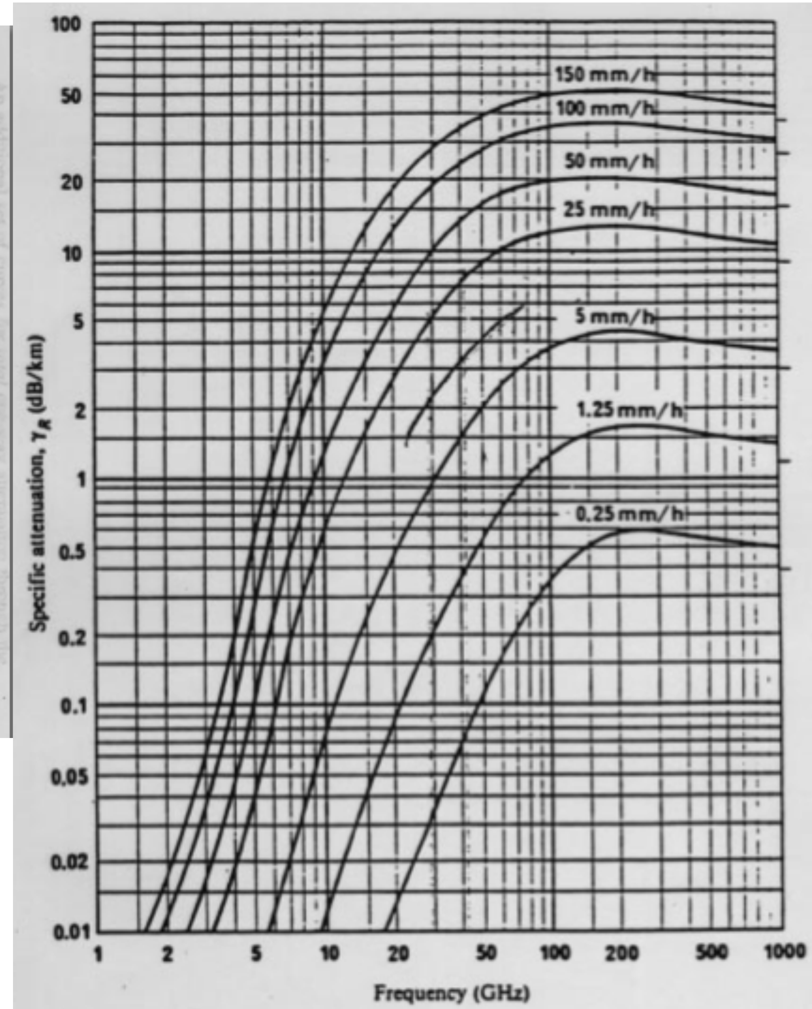


Figure10: Specific Attenuation Due to Rain.

Oxygen absorption
16 dB/km at 60 GHz

Rain hits all mm wave freqs badly
~ 20 dB/km at 50 mm/hr

Millimeter Wave Propagation: Spectrum Management Implications, FCC Bulletin 70, Juy 1997

What not fighting physics means

- Must use directional TX and RX
  - Hence electronically steerability is key if we want flexible usage
- Must steer around, not burn through, obstacles
  - Hence electronic steerability is key if we want robust usage
- Should not shoot for kilometers range
  - 16 dB/km (O2) or 20 dB/km (rain) or 36 dB/km (both) are all bad news
- But can certainly go well beyond indoor WPAN
  - Oxygen absorption + heavy rain costs only 3.6 dB at 100m

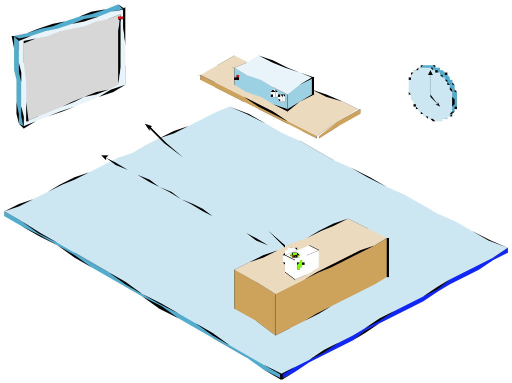
What applications are consistent with these guidelines?

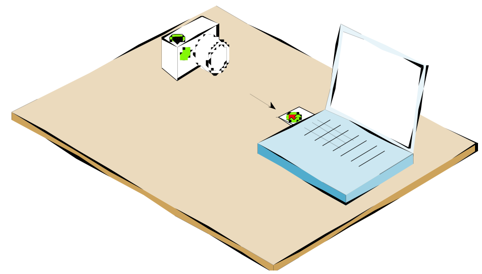
Example applications

Consistent with the physics

Consistent with mass market economics

Indoor focus over the past few years



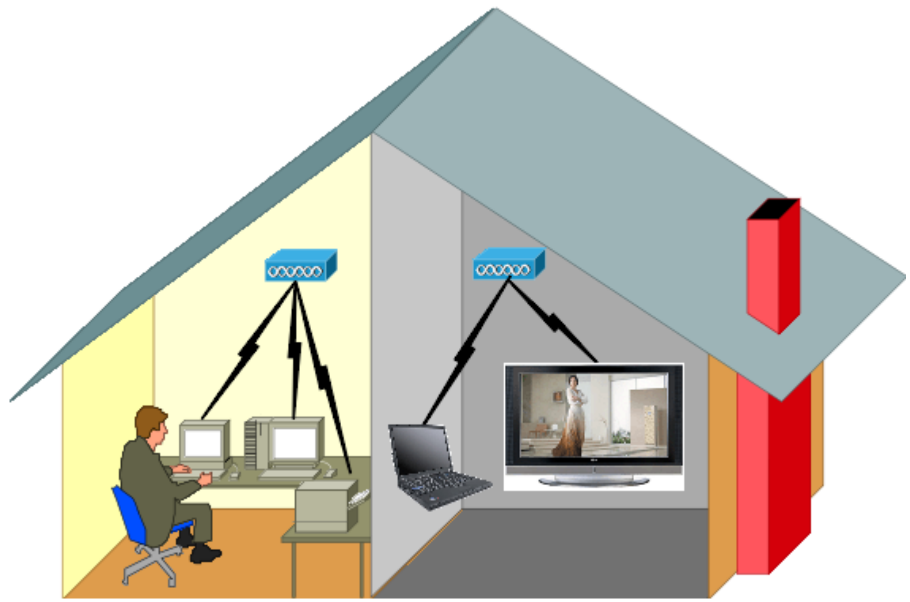


WiGig/IEEE 802.11ad

Up to 7 Gbps
In room
Up to 10m

⇓

60 GHz CMOS RFICs
Antenna array in package (32 elt)
Directional MAC



Showed feasibility of steering around obstacles

But is mm wave comm just nice to have?

- 802.11n is pretty fast already
- Once we upgrade WLAN speeds to a few Gbps, are we done?
- Not quite…
- Millimeter wave communication can play a crucial role in today's cellular capacity crunch

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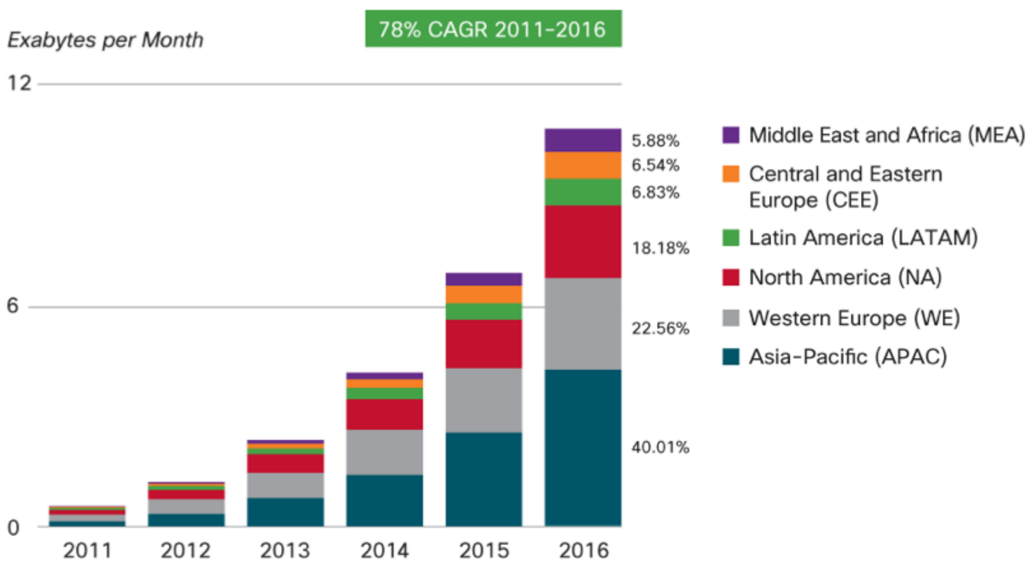
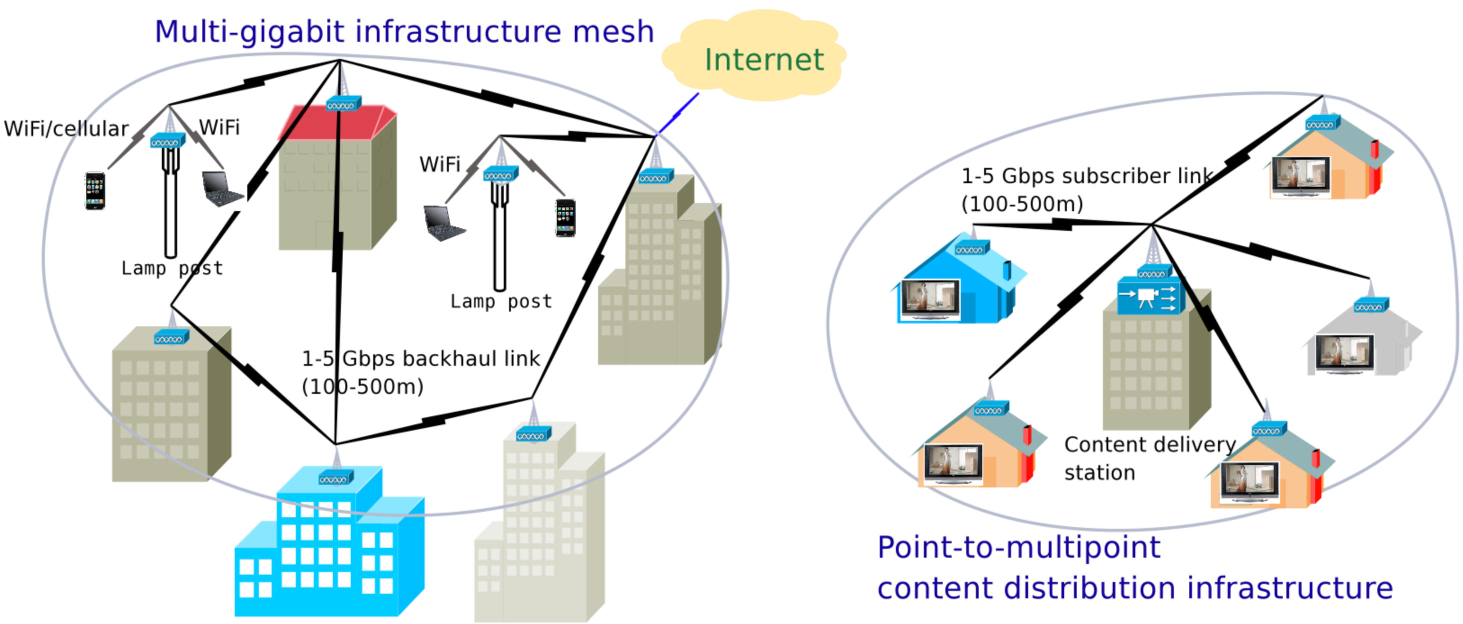


Source: Cisco VNI Mobile, 2012

mm wave for small cells, stage 1

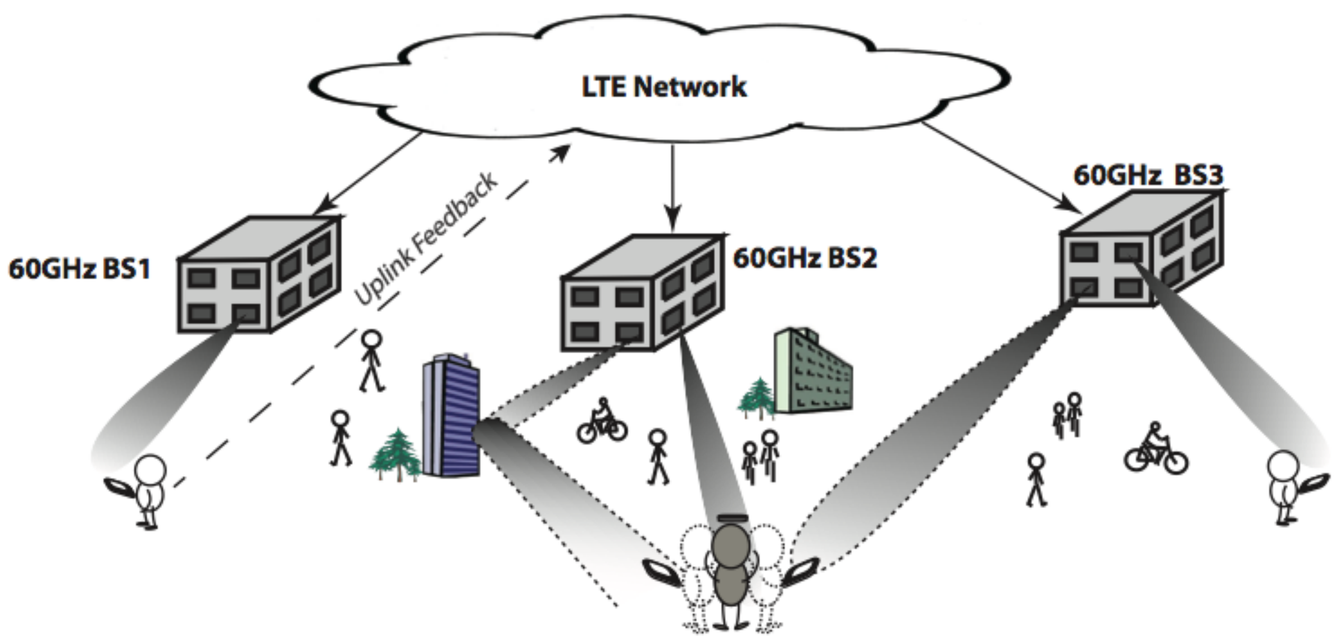
- Increase cellular capacity by drastically increasing spatial reuse
  – Base stations on lampposts, 200 m cell size
  – 4G to mobile, mm wave between base stations
- MultiGigabit wireless mesh backhaul enables dense picocell deployments



Need flexible beamsteering to form mesh
Need five 9s reliability for backhaul

mm wave for small cells, stage 2

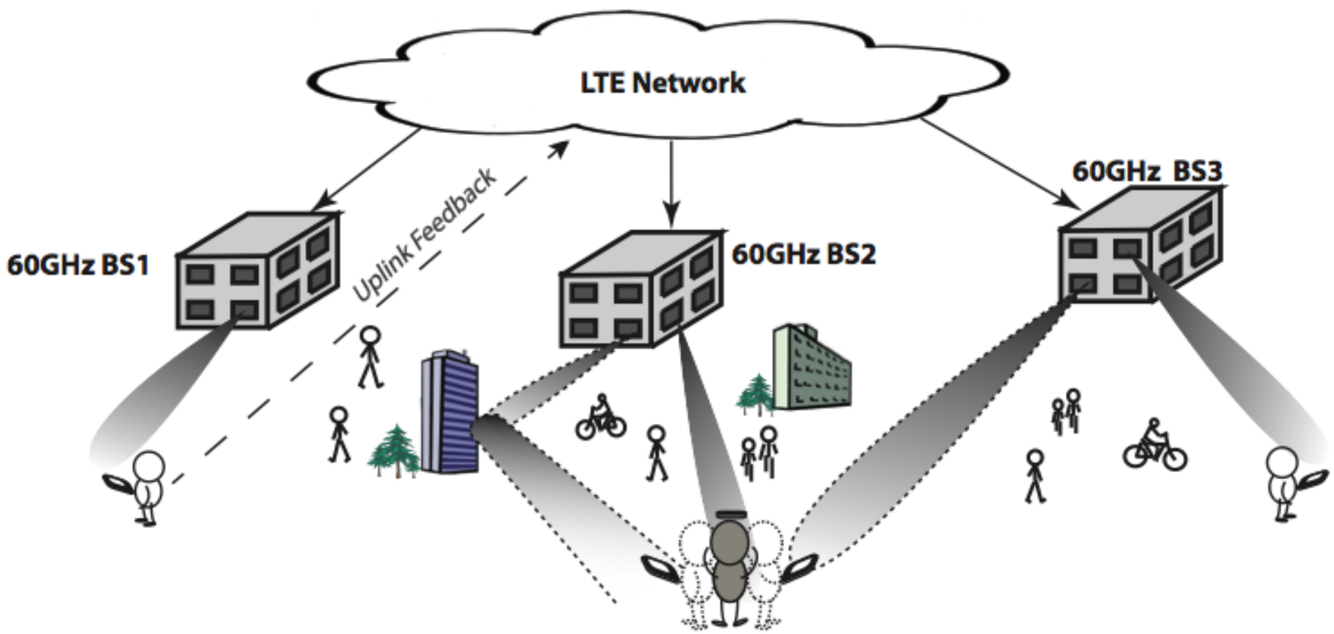
- Up the ante on spatial reuse
  - Highly directional mm wave (+LTE) to the mobile
  - 28 GHz being pushed as a possibility
  - Alternative: Downlink 60 GHz with uplink LTE feedback
  - Leverage WiGig radio on mobile device in receive-only model



Need robustness to blockage by user's body and other obstacles

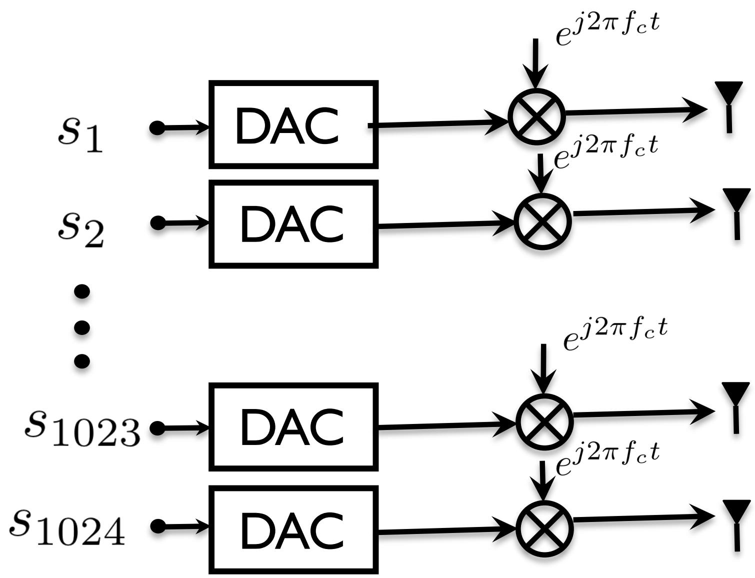
Focus today: Beamsteering with very large arrays

(The key to "unlimited" spatial reuse)



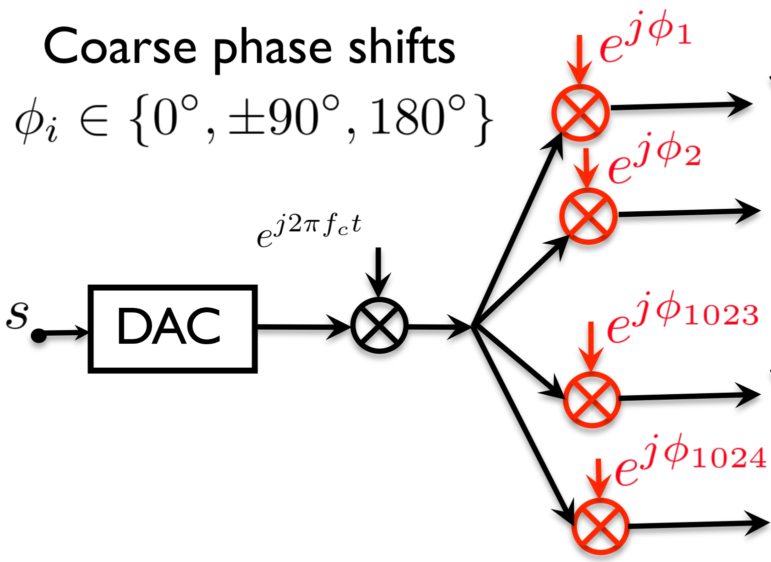
Beamforming today

DSP-centric, one RF chain per antenna element



Does not scale to 1000 elements!

RF Beamforming with hardware constraints

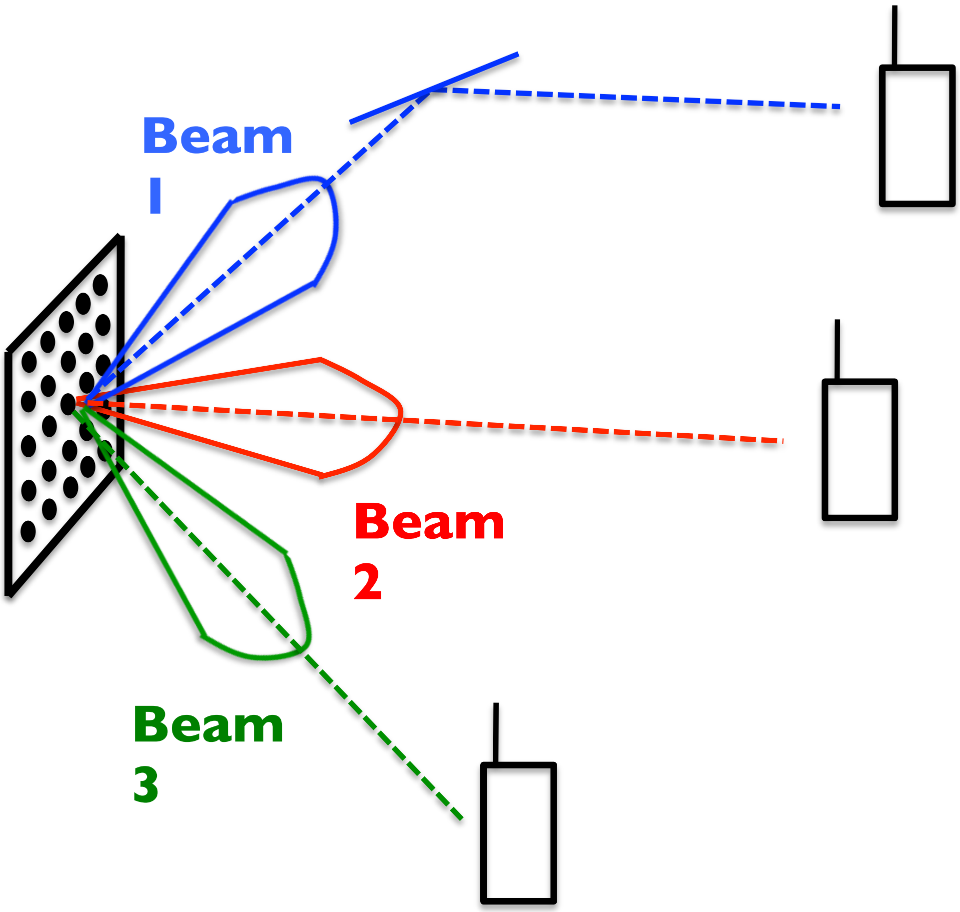


Much more feasible

But how do we adapt it?

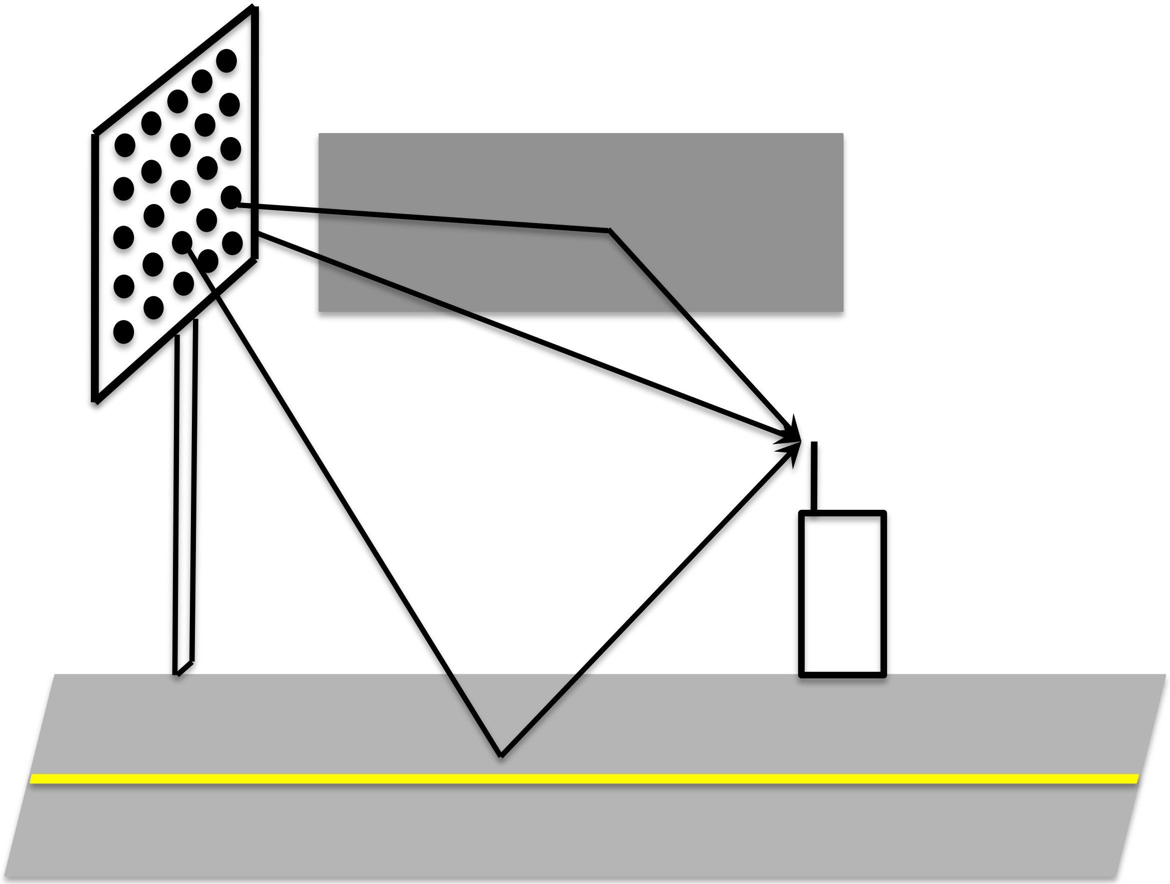
No access to individual elements ➔ least squares does not work

Beam scanning architecture unattractive

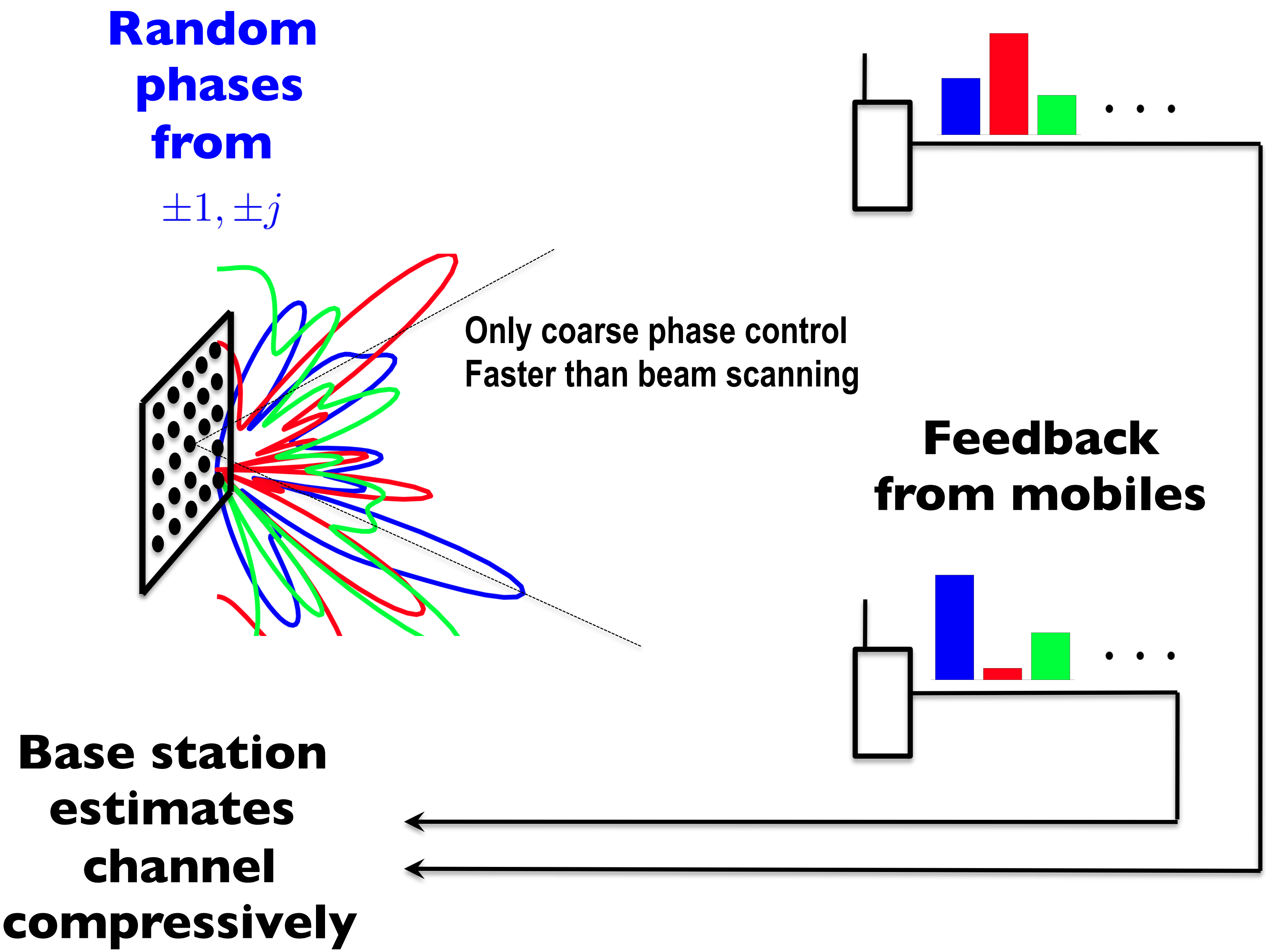


- Requires fine control of phases
- Slow adaptation

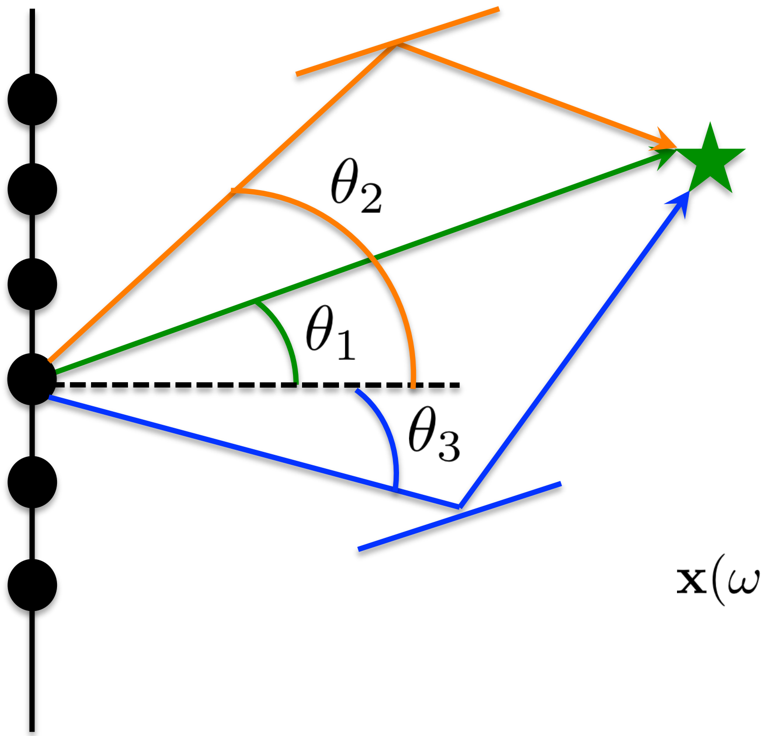
Can we use the sparsity of the mm wave channel?



Compressive adaptation



Estimation problem



Channel is a sum of a few sinusoids

$$\mathbf{h} = g_1\mathbf{x}(\omega_1) + g_2\mathbf{x}(\omega_2) + g_3\mathbf{x}(\omega_3)$$

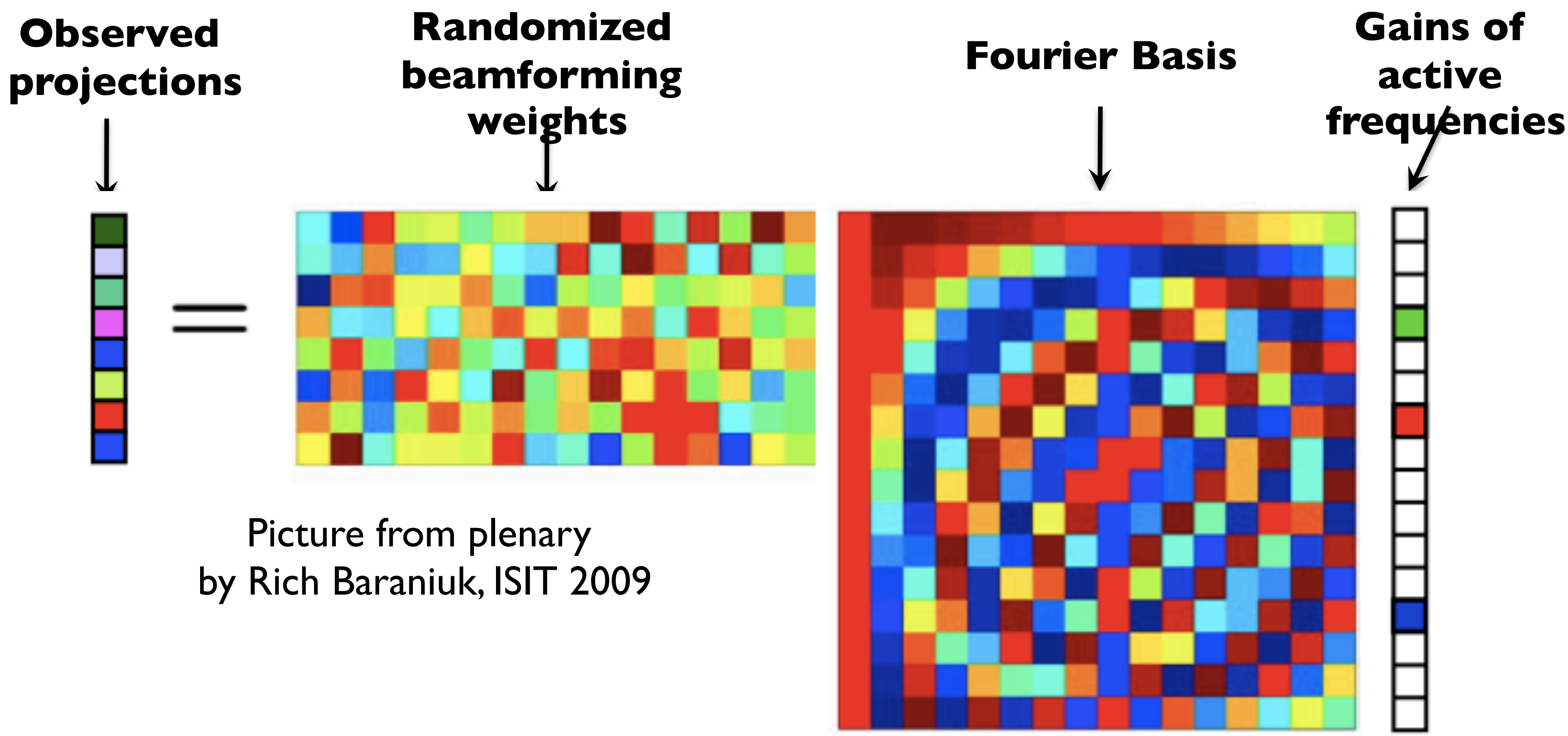
$$\mathbf{x}(\omega) = \begin{pmatrix} 1 \\ e^{j\omega} \\ e^{j2\omega} \\ \vdots \\ e^{j(N-1)\omega} \end{pmatrix} \qquad \omega_i = \frac{2\pi d}{\lambda}\sin\theta_i$$

Mobile makes compressive measurements

$$y_i = \mathbf{a}_i^T\mathbf{h}, i = 1, 2, \ldots, M$$

Estimate gains and spatial frequencies from compressive measurements

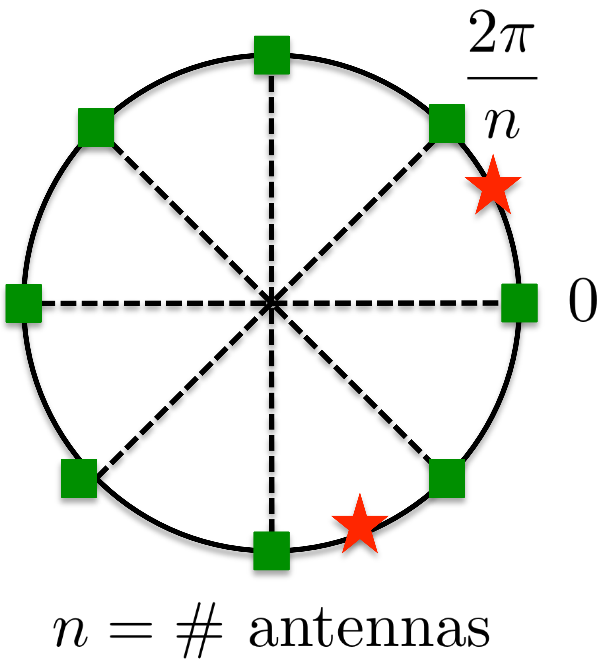
Can we use standard compressed sensing?



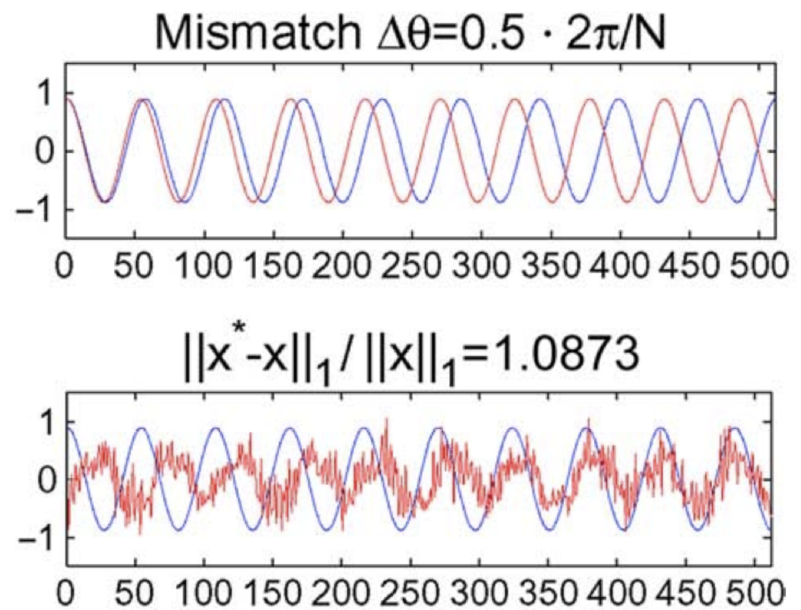
Picture from plenary
by Rich Baraniuk, ISIT 2009

$$\mathbf{y} = \sum_{k=1}^{L} g_k \mathbf{A}\mathbf{x}(\omega_k) + \mathbf{n}$$

Not quite: basis mismatch is the problem



Frequencies come from a continuum, not a grid



With standard CS, off-grid frequencies can have large estimation errors

Sensitivity to Basis Mismatch in Compressed Sensing, Y. Chi, L. Scharf, A. Pezeshki, R. Calderbank

Need a new theory of compressive estimation!

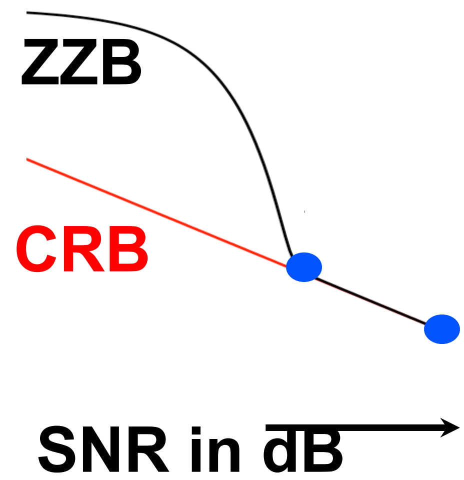
Compressive estimation in AWGN

Ramasamy, Venkateswaran, Madhow, "Compressive Parameter Estimation in AWGN," IEEE Transactions on Signal Processing, April 2014

Standard parameter estimation

$$\mathbf{y} = \mathbf{s}(\boldsymbol{\theta}) + \mathbf{z}, \ \mathbf{z} \sim \mathcal{CN}(\mathbf{0}, \sigma^2 \mathbb{I}_M)$$

$$\widehat{\theta}_{\mathrm{ML}} = \arg\min_{\theta} \| \mathbf{y} - \mathbf{s}(\theta) \|$$



Performance measures

Cramer-Rao Bound (CRB) when close to truth

Ziv-Zakai bound (ZZB) more generally
(are you in the right bin? How close, once in the right bin?)

ZZB tends to CRB at high SNR (high prob of right bin).
This is when estimation can be expected to “work well.”

Performance depends on Euclidean distances

CRB depends on Fisher Information Matrix

$$F_{m,n}(\boldsymbol{\theta}) = \frac{2}{\sigma^2} \Re \left\{ \left(\frac{\partial \mathbf{s}(\boldsymbol{\theta})}{\partial \theta_m} \right)^H \frac{\partial \mathbf{s}(\boldsymbol{\theta})}{\partial \theta_n} \right\}$$

Depends on changes in signal geometry for small changes in parameter

Ziv-Zakai bound is based on an associated detection problem

$$H_1 : \mathbf{y} = \mathbf{s}(\boldsymbol{\theta}_1) + \mathbf{z}, \ \Pr(H_1) = \frac{p(\boldsymbol{\theta}_1)}{p(\boldsymbol{\theta}_1) + p(\boldsymbol{\theta}_2)}$$

$$H_2 : \mathbf{y} = \mathbf{s}(\boldsymbol{\theta}_2) + \mathbf{z}, \ \Pr(H_2) = \frac{p(\boldsymbol{\theta}_2)}{p(\boldsymbol{\theta}_1) + p(\boldsymbol{\theta}_2)}.$$

Depends on changes in signal geometry for general changes in parameter

$$d(\boldsymbol{\theta}_1, \boldsymbol{\theta}_2) = ||\mathbf{s}(\boldsymbol{\theta}_1) - \mathbf{s}(\boldsymbol{\theta}_2)||$$

Compressive measurements: model

High-dimensional signal space $\mathbf{x}(\boldsymbol{\theta}) \in \mathbb{R}^N$

(but unknown parameter lies in low-dimensional space)

M compressive measurements

$$y_i = \langle\ \mathbf{w}_i\ ,\ \mathbf{x}(\boldsymbol{\theta}_t) + \mathbf{z}_i\ \rangle$$

$$\boldsymbol{A} = [\mathbf{w}_1\ \cdots\ \mathbf{w}_M]^T$$

$$\mathbf{y} = \boldsymbol{A}\mathbf{x}(\boldsymbol{\theta}_t) + \mathbf{z}$$

$$\mathbf{z}_i \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbb{I}_N)$$

Noise power is same

$$\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbb{I}_M)$$

When does this provide the “same” performance as standard estimation?

Compressive estimation works well when

1) Signal space geometry is preserved

(similar to RIP for compressive sensing)

2) "Effective SNR" is high enough

The structure of compressive estimation

UCSB

GENERAL STRUCTURE

1) Required isometries
CRB: Preserve distance changes under small perturbations
ZZB: Preserve distance changes generally

2) SNR penalty (➔ "effective SNR")
Dimension reduction from N to M ➔ SNR reduction by M/N

3) Definition of "working well"
ZZB tends to CRB (coarse errors highly unlikely)

PROBLEM-SPECIFIC ANALYSIS

How many observations needed to preserve isometries?

Isometries needed

Tangent plane isometry (for CRB)

$$\sqrt{\frac{M}{N}}(1-\epsilon) \leq \frac{\|\boldsymbol{A}\sum a_m(\partial \mathbf{x}(\boldsymbol{\theta})/\partial\theta_m)\|}{\|\sum a_m(\partial \mathbf{x}(\boldsymbol{\theta})/\partial\theta_m)\|} \leq \sqrt{\frac{M}{N}}(1+\epsilon)$$

$$\forall\,[a_1, a_2, \ldots, a_K]^T \in \mathbb{R}^K \backslash \{\mathbf{0}\},\ \forall \boldsymbol{\theta} \in \Theta$$

Pairwise ε-isometry (for ZZB)

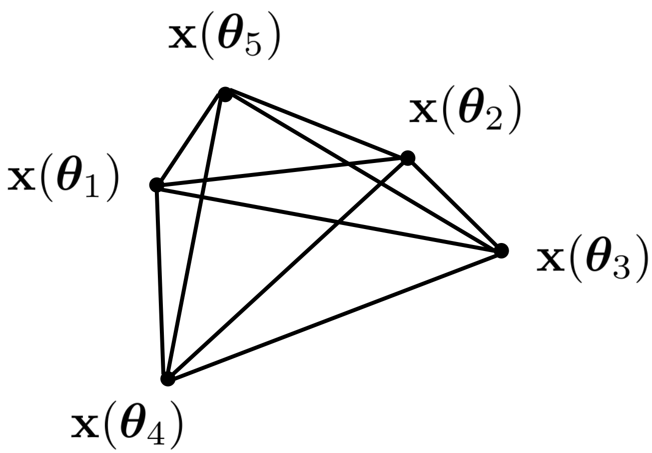
$$\sqrt{\frac{M}{N}}(1-\epsilon) \leq \frac{\|\boldsymbol{A}\mathbf{x}(\boldsymbol{\theta}_1) - \boldsymbol{A}\mathbf{x}(\boldsymbol{\theta}_2)\|}{\|\mathbf{x}(\boldsymbol{\theta}_1) - \mathbf{x}(\boldsymbol{\theta}_2)\|} \leq \sqrt{\frac{M}{N}}(1+\epsilon)$$

$$\forall\, \boldsymbol{\theta}_1, \boldsymbol{\theta}_2 \in \Theta.$$

What geometry preservation looks like

All measurements

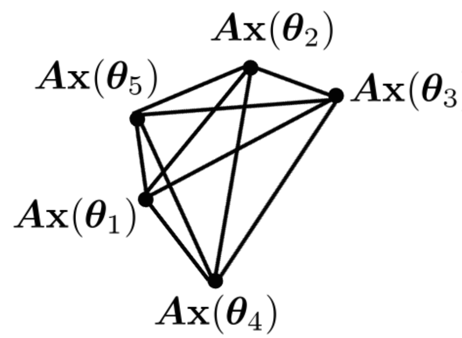
$$\mathbf{y} = \mathbf{x}(\boldsymbol{\theta}_t) + \mathbf{z} \qquad \mathbf{z} \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbb{I}_N)$$



$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}_i} \|\mathbf{y} - \mathbf{x}(\boldsymbol{\theta}_i)\|^2$$

Compressive measurements

$$\mathbf{y} = \boldsymbol{A}\mathbf{x}(\boldsymbol{\theta}_t) + \mathbf{z} \qquad \mathbf{z} \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbb{I}_M)$$



$\in \mathbb{R}^M$

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}_i} \|\mathbf{y} - \boldsymbol{A}\mathbf{x}(\boldsymbol{\theta}_i)\|^2$$

Why we can hope for geometry preservation

$$\mathbf{v} = \mathbf{x}(\boldsymbol{\theta}_i) - \mathbf{x}(\boldsymbol{\theta}_j)$$

- Random projections must preserve norm of

$$\frac{1}{M}\|\boldsymbol{A}\mathbf{v}\|^2 = \frac{1}{M}\sum_{i=1}^{i=M} |\mathbf{w}_i^T \mathbf{v}|^2 \xrightarrow[\text{concentrates}]{M \text{ large enough}} \text{Mean} \quad (1/N)\|\mathbf{v}\|^2$$

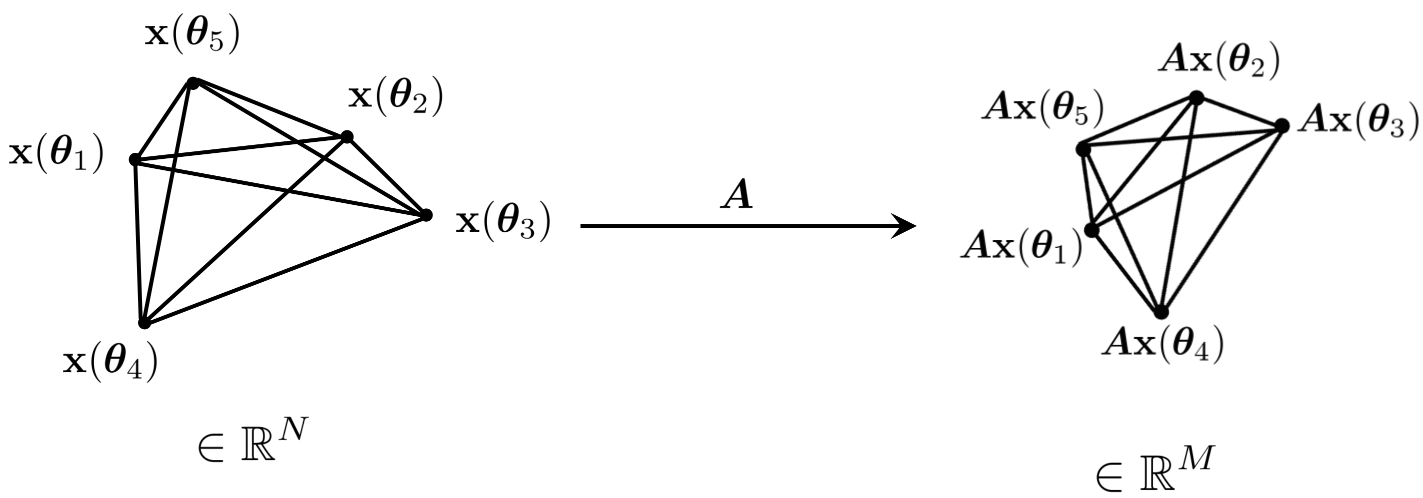
i.i.d. with mean $(1/N)\|\mathbf{v}\|^2$

- Chernoff bound on deviations from the mean (with tolerance ε) + Union bound (for all pairwise differences)

Johnson-Lindenstrauss (JL) Lemma

Achlioptas, "Database-friendly Random Projections", 2001

How many measurements?



Johnson-Lindenstrauss (JL) lemma:
Pairwise ε-isometry for *finite* signal model $\mathcal{H} = \{\mathbf{x}(\boldsymbol{\theta}_i)\}$ when the number of random projections :

$$M = O\left(\epsilon^{-2} \log |\mathcal{H}|\right)$$

K signals, M measurements

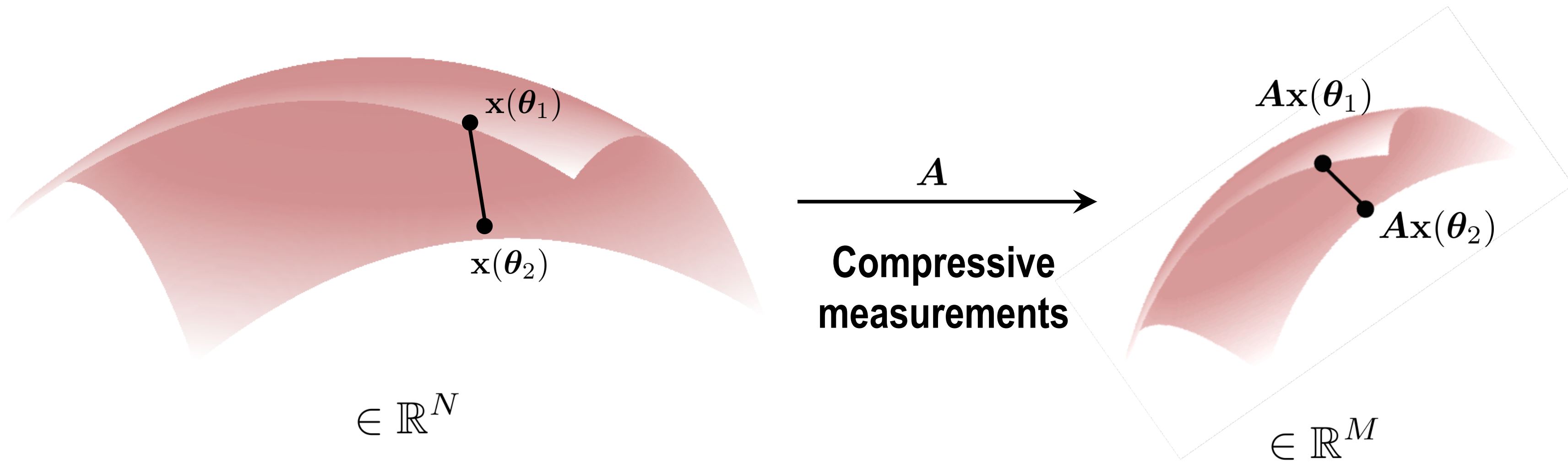
Chernoff bound + Union bound $\sim K^2 e^{-\alpha M}$

$\Rightarrow M = O(\log K)$

Continuous signal model

Parameters come from a continuum $\boldsymbol{\theta} \in \mathbb{R}^K$

Need pairwise isometries for all $(\boldsymbol{\theta}_1, \boldsymbol{\theta}_2)$ pairs



Cannot directly use JL lemma

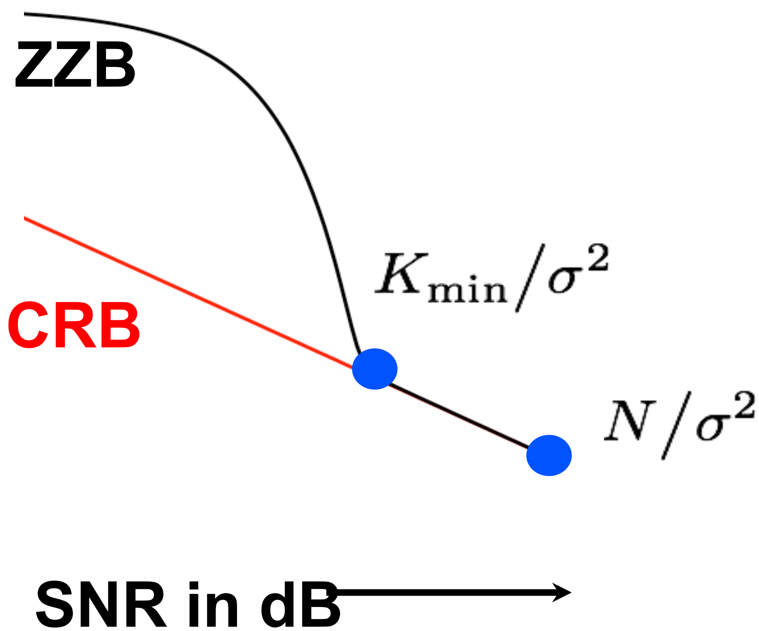
But discretization, JL lemma, and smoothness can be used to do the trick

How many measurements for good performance?

- If pairwise isometry holds, then both CRLB and ZZB go through

➔ Only effect of compressive measurements is SNR reduction

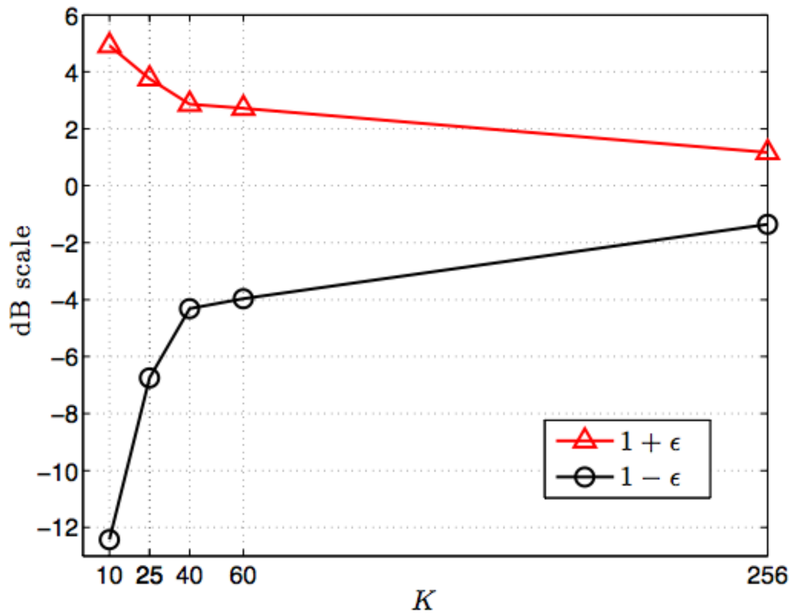
- Number of measurements must satisfy two criteria for good performance
  - Should be enough to provide pairwise isometry
  - Effective SNR should be such that ZZB tends to CRLB

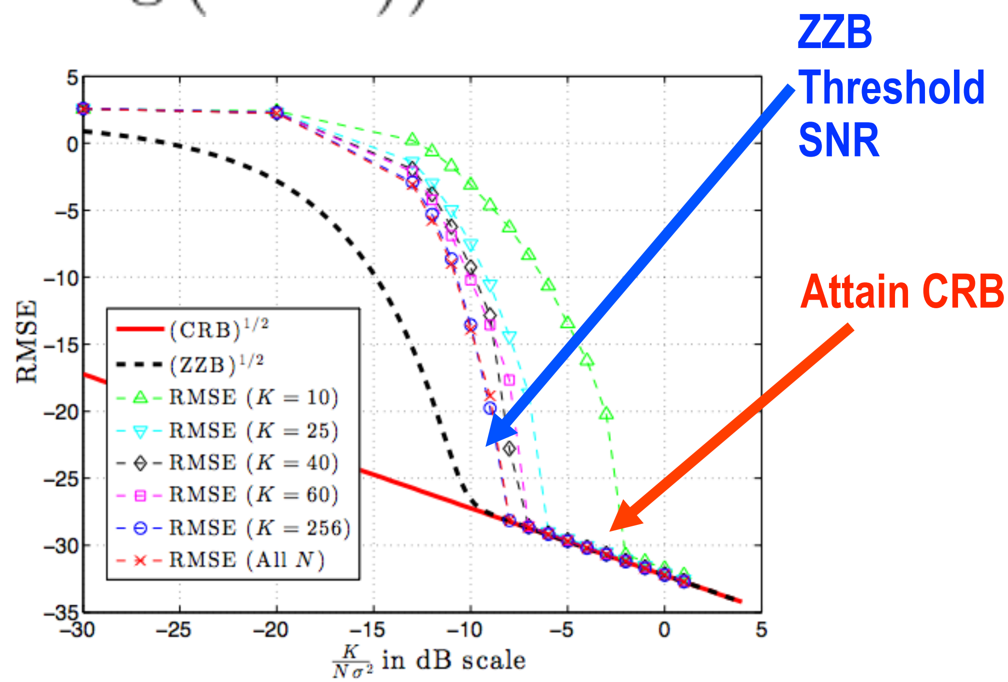


Attaining the CRB for a sinusoid

Problem-specific analysis → Pairwise isometry requires

$$K = O\left(\epsilon^{-2}\log\left(N\epsilon^{-1}\right)\right)$$





More random projections
Better isometry constants →

Effective SNR →

RMSE performance for 40+ measurements closely follows that for all N=256 measurements
Isometry constants good for 40+ measurements

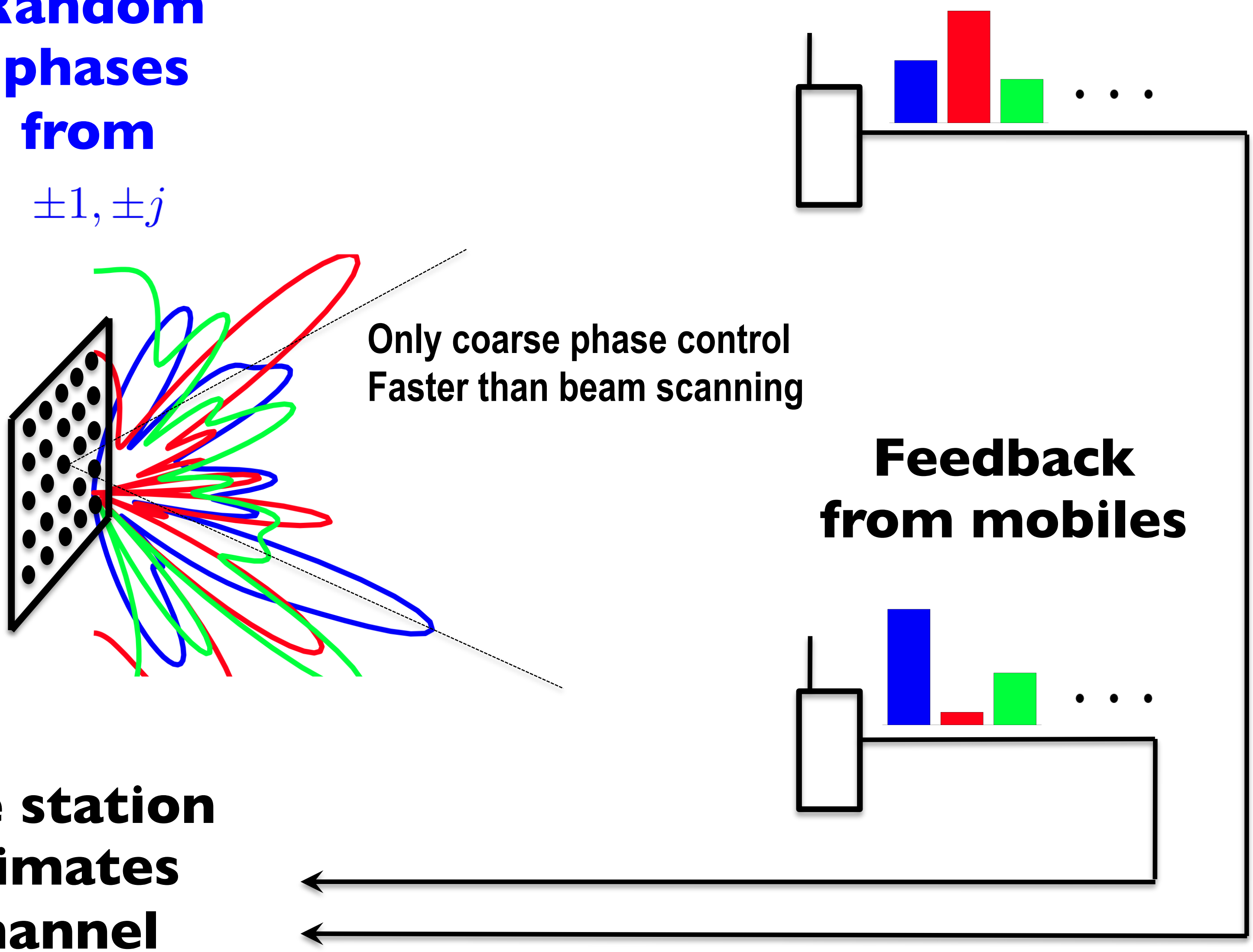
$$K = \min(40, \text{ZZB threshold SNR} \times N\sigma^2)$$

Back to the application at hand

How to estimate a 1000-dimensional spatial channel?

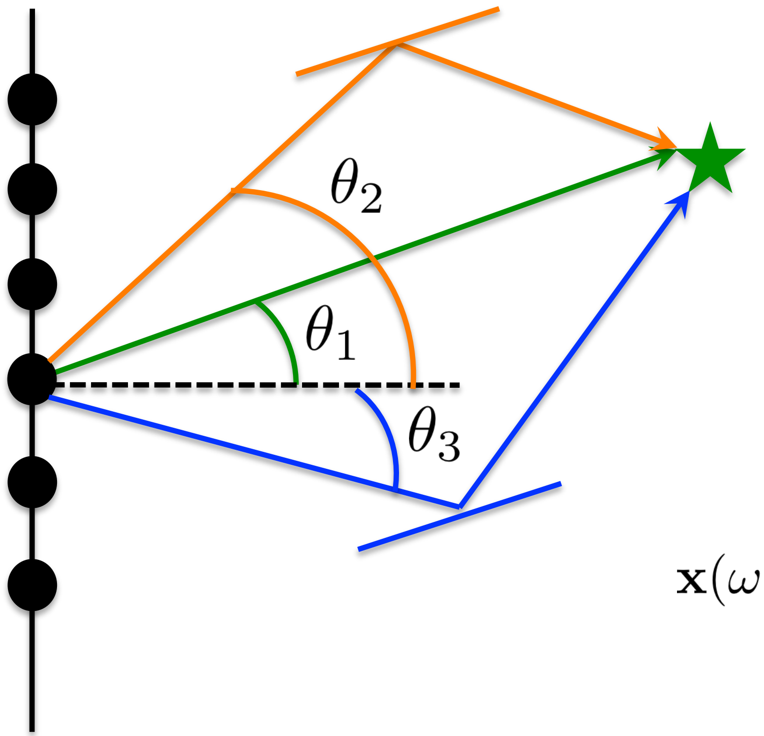
Compressive adaptation

Random phases from $\pm 1, \pm j$



Base station estimates channel compressively

Estimation problem



Channel is a sum of a few sinusoids

$$\mathbf{h} = g_1 \mathbf{x}(\omega_1) + g_2 \mathbf{x}(\omega_2) + g_3 \mathbf{x}(\omega_3)$$

$$\mathbf{x}(\omega) = \begin{pmatrix} 1 \\ e^{j\omega} \\ e^{j2\omega} \\ \vdots \\ e^{j(N-1)\omega} \end{pmatrix} \quad \omega_i = \frac{2\pi d}{\lambda} \sin \theta_i$$

Mobile makes compressive measurements

$$y_i = \mathbf{a}_i^T \mathbf{h}, i = 1, 2, \ldots, M$$

Estimate gains and spatial frequencies from compressive measurements

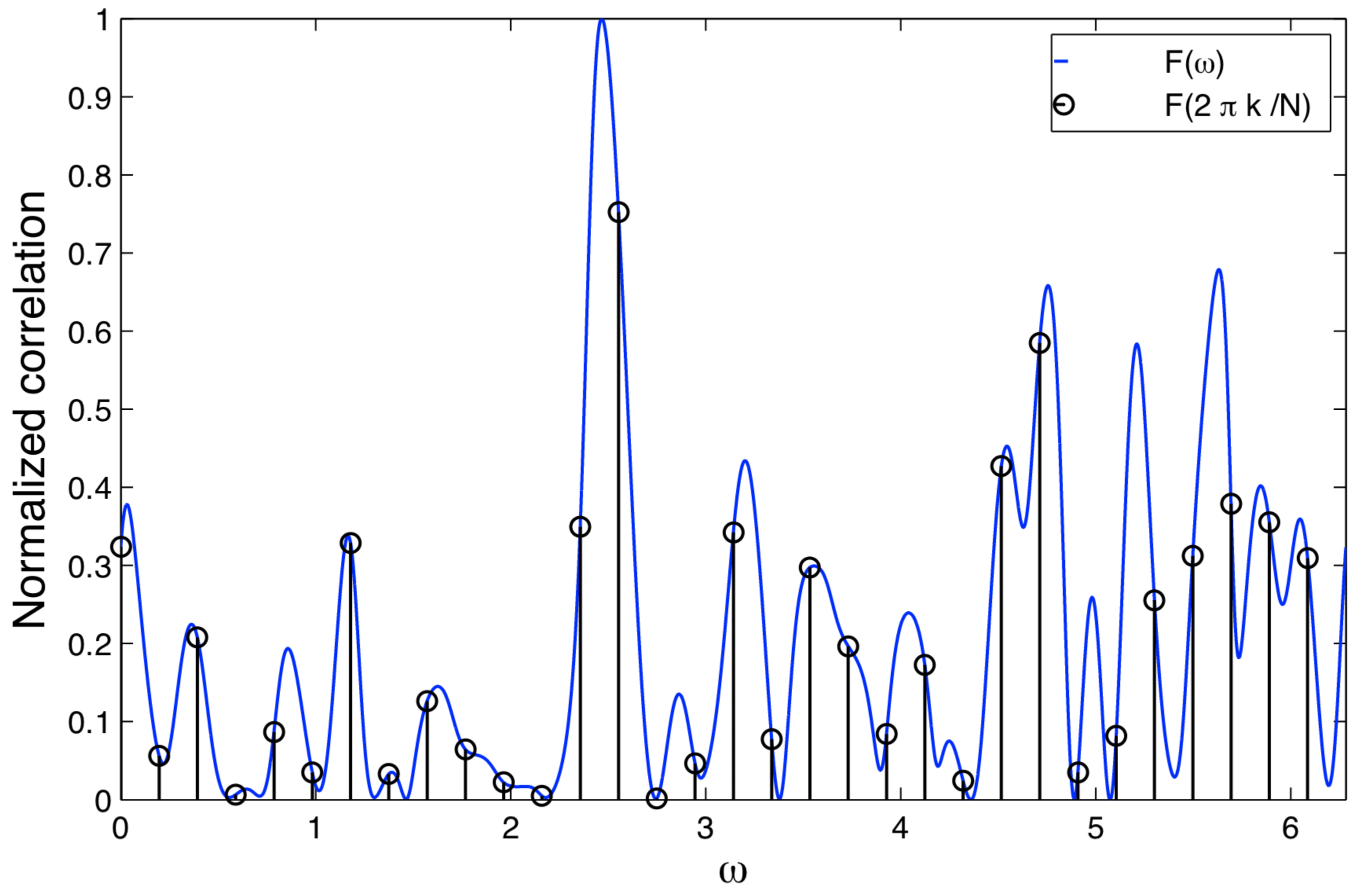
Algorithm

- Acquisition
  - No knowledge of spatial frequencies whatsoever
- Tracking
  - Leverage frequency estimate from previous round
  - Refine based on new measurements

Acquisition: Coarse Estimate

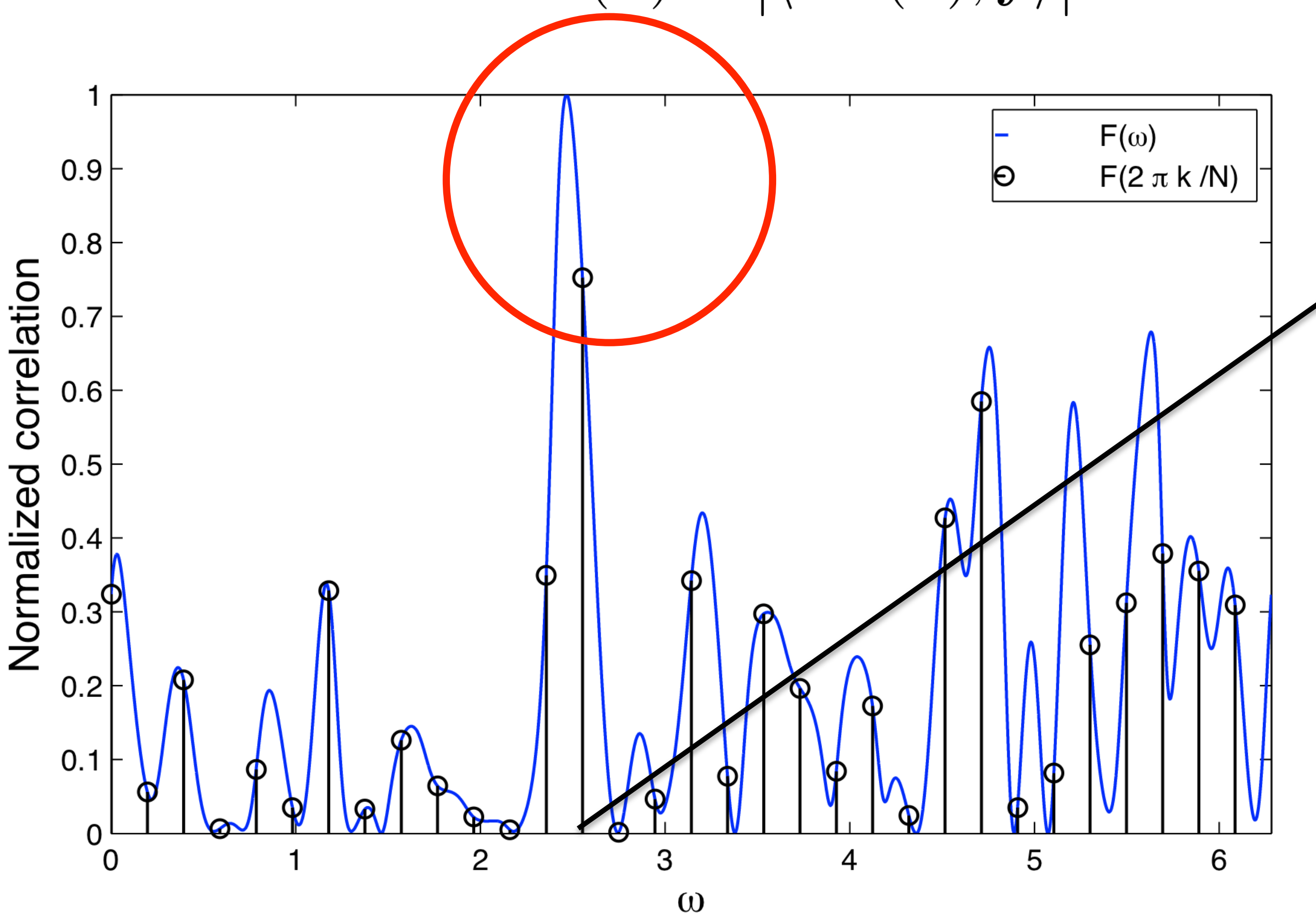
$$\text{maximize } F(\omega) = \left|\langle \mathbf{A}\mathbf{x}(\omega), \mathbf{y}\rangle\right|^2$$

$$\omega = 0, \frac{2\pi}{2N}, 2\left(\frac{2\pi}{2N}\right), \ldots, (2N-1)\left(\frac{2\pi}{2N}\right)$$



Acquisition: Coarse Estimate

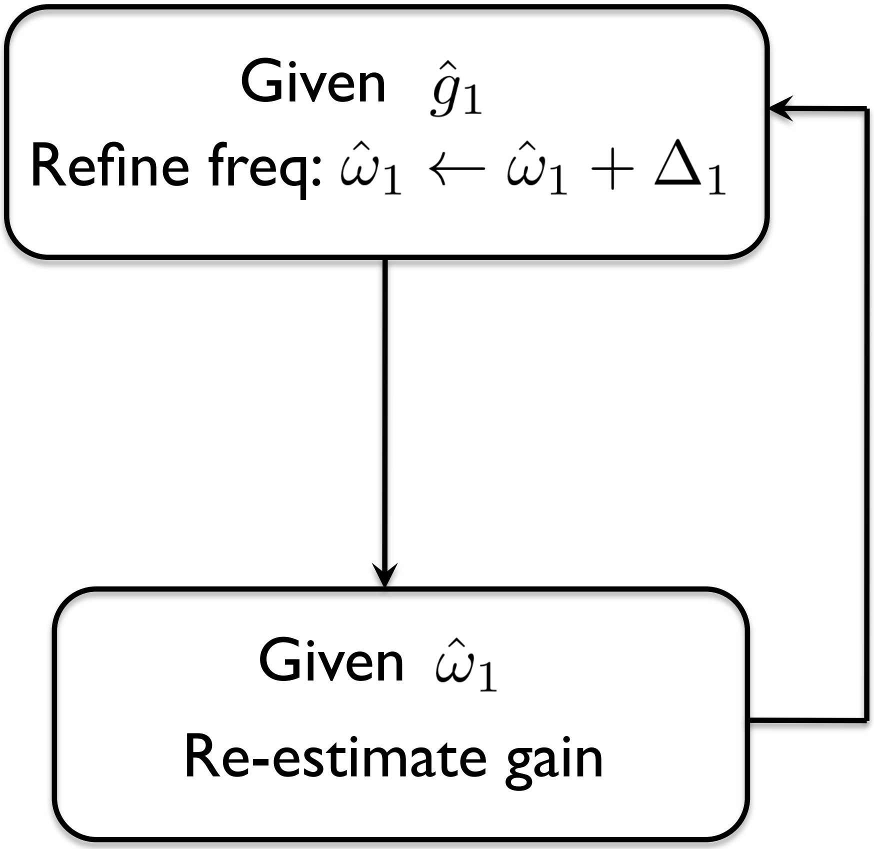
$$\text{maximize } F(\omega) = \left|\langle \mathbf{Ax}(\omega), \mathbf{y} \rangle\right|^2$$



$$\hat{\omega}_1$$

$$\hat{g}_1 = \frac{\langle \mathbf{Ax}(\hat{\omega}_1), \mathbf{y} \rangle}{\|\mathbf{Ax}(\hat{\omega}_1)\|^2}$$

Acquisition: Refine Estimate



$$\mathbf{y} = \hat{g}_1 \mathbf{A}\mathbf{x}(\hat{\omega}_1 + \Delta_1) + \mathbf{n}$$

$$[\mathbf{y} - \hat{g}_1 \mathbf{A}\mathbf{x}(\hat{\omega}_1)] = \left[\hat{g}_1 \mathbf{A} \frac{d\mathbf{x}(\hat{\omega}_1)}{d\omega}\right] \Delta_1 + \mathbf{n}$$

$$\Delta_1 \in \mathbb{R}$$

$$\mathbf{y} = g_1 \mathbf{A}\mathbf{x}(\hat{\omega}_1) + \mathbf{n}$$

Multiple Frequencies

Given

Gains: $\hat{g}_1, \hat{g}_2, \ldots, \hat{g}_K$

Freqs: $\hat{\omega}_1, \hat{\omega}_2, \ldots, \hat{\omega}_K$

↓

Project out contributions from these frequencies

$$\mathcal{S} = \mathbf{A}\left[\mathbf{x}(\hat{\omega}_1)\ \mathbf{x}(\hat{\omega}_2) \ldots \mathbf{x}(\hat{\omega}_K)\right]$$

$$\mathbf{y}_r = \mathcal{S}^{\perp}\mathbf{y}$$

↓

Coarsely estimate (K+1)th freq

$$\max_{\omega = 0, \frac{2\pi}{2N}, 2\left(\frac{2\pi}{2N}\right), \ldots, (2N-1)\left(\frac{2\pi}{2N}\right)} |\langle \mathbf{A}\mathbf{x}(\omega), \mathbf{y}_r \rangle|^2$$

$$\hat{\omega}_{K+1}, \hat{g}_{K+1}$$

↓

Fix gains: $\hat{g}_1, \hat{g}_2, \ldots, \hat{g}_K, \hat{g}_{K+1}$

Refine freqs: $\Delta_1, \Delta_2, \ldots, \Delta_{K+1}$

↓

Fix freqs: $\hat{\omega}_1, \hat{\omega}_2, \ldots, \hat{\omega}_{K+1}$

Estimate g's: $\hat{g}_1, \hat{g}_2, \ldots, \hat{g}_K, \hat{g}_{K+1}$

Multiple Frequencies

$$\mathbf{y} - \sum_{l=1}^{K+1} \hat{g}_l \mathbf{A}\mathbf{x}(\hat{\omega}_l)$$

$$||$$

$$\mathbf{A}\left[\hat{g}_1 \frac{d\mathbf{x}(\hat{\omega}_1)}{d\omega} \;\; \ldots \;\; \hat{g}_{K+1} \frac{d\mathbf{x}(\hat{\omega}_{K+1})}{d\omega}\right] \begin{pmatrix} \Delta_1 \\ \Delta_2 \\ \vdots \\ \Delta_{K+1} \end{pmatrix}$$

$$\mathbf{y} = \mathbf{A}\left[\mathbf{x}(\hat{\omega}_1) \;\; \ldots \;\; \mathbf{x}(\hat{\omega}_{K+1})\right] \begin{pmatrix} g_1 \\ g_2 \\ \vdots \\ g_{K+1} \end{pmatrix}$$

Coarsely estimate (K+1)th freq

$$\max_{\omega = 0, \frac{2\pi}{2N}, 2\left(\frac{2\pi}{2N}\right), \ldots, (2N-1)\left(\frac{2\pi}{2N}\right)} |\langle \mathbf{A}\mathbf{x}(\omega), \mathbf{y}_r \rangle|^2$$

$$\hat{\omega}_{K+1}, \hat{g}_{K+1}$$

↓

Fix gains: $\hat{g}_1, \hat{g}_2, \ldots, \hat{g}_K, \hat{g}_{K+1}$

Refine freqs: $\Delta_1, \Delta_2, \ldots, \Delta_{K+1}$

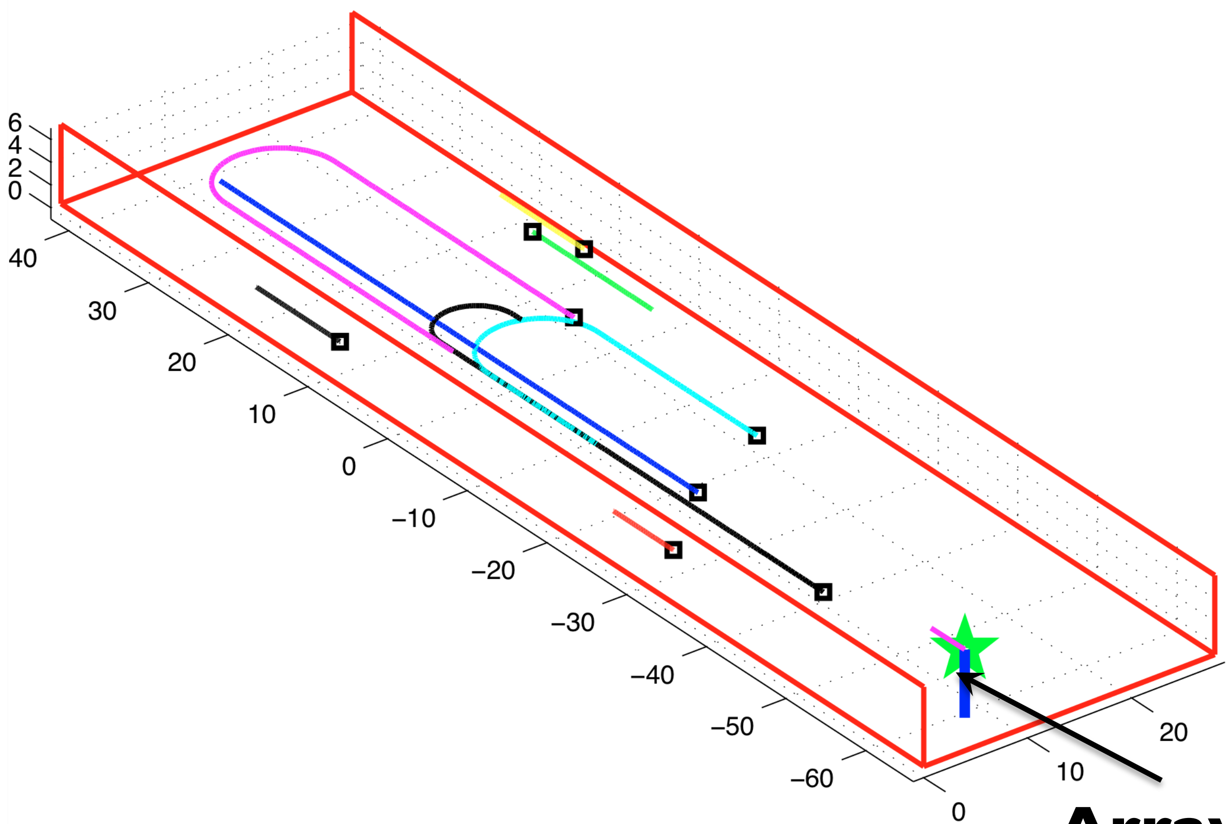
↓

Fix freqs: $\hat{\omega}_1, \hat{\omega}_2, \ldots, \hat{\omega}_{K+1}$

Estimate g's: $\hat{g}_1, \hat{g}_2, \ldots, \hat{g}_K, \hat{g}_{K+1}$

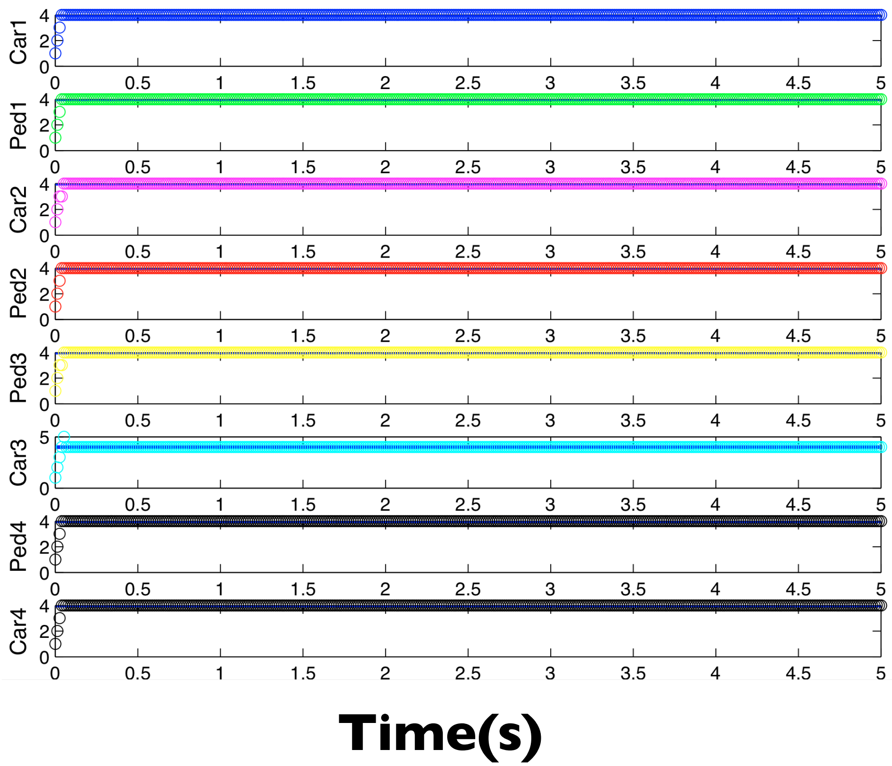
Same algorithm works for tracking, just bootstrap with estimate from prior round

Simulation Setup

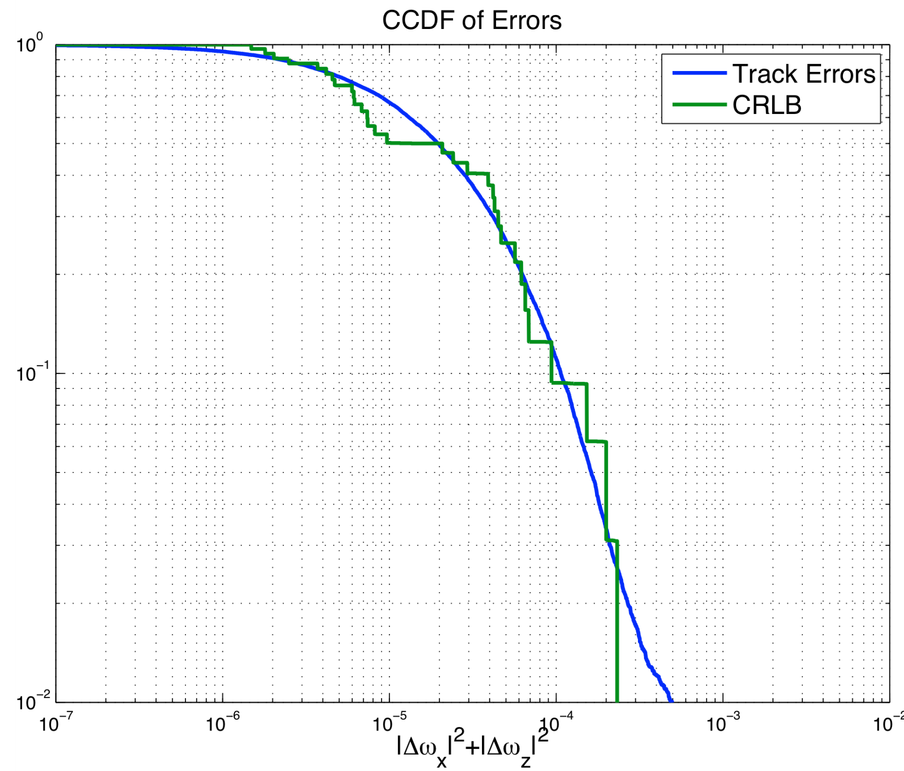


Array on lamp post

Results



Estimated number of beams



Estimation errors close to CRB

Take-aways from this case study

- Unique challenges of adapting large mm wave arrays

➔ Compressive adaptation approach

➔ New theory of compressive estimation

- New insight on algorithms attaining CRB
  - Coarse grid, then gradient or Newton based refinement does work

  (If SNR is high enough to get past ZZB threshold)

- Specific motivating application, but leads to rather general techniques

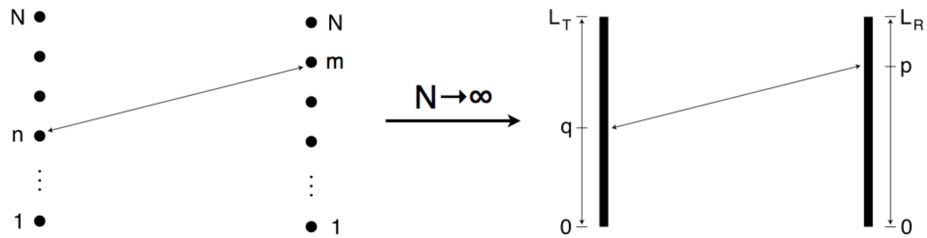
This is only the beginning...

A sampling of new and exciting problems in SPAWC

New MIMO paradigms

LoS MIMO: fundamentals

- MIMO at small carrier wavelengths does not need “rich scattering”
  - Degrees of freedom depend on form factor



$$y_m = \frac{1}{N}\sum_{n=1}^{N} \underbrace{\exp\left(-i\frac{\pi}{\lambda R}(nd_T - md_R)^2\right)}_{h_{m,n}} x_n \qquad y(p) = \frac{1}{L_T}\int_{-L_T/2}^{L_T/2} \underbrace{\exp\left(-i\frac{\pi}{\lambda R}(q-p)^2\right)}_{h(q,p)} x(q)\mathrm{d}q$$

$$\lambda_n \phi_n(t) = \int_{-T/2}^{T/2} \frac{\sin 2\pi W(t-s)}{\pi(t-s)} \phi_n(s)ds$$

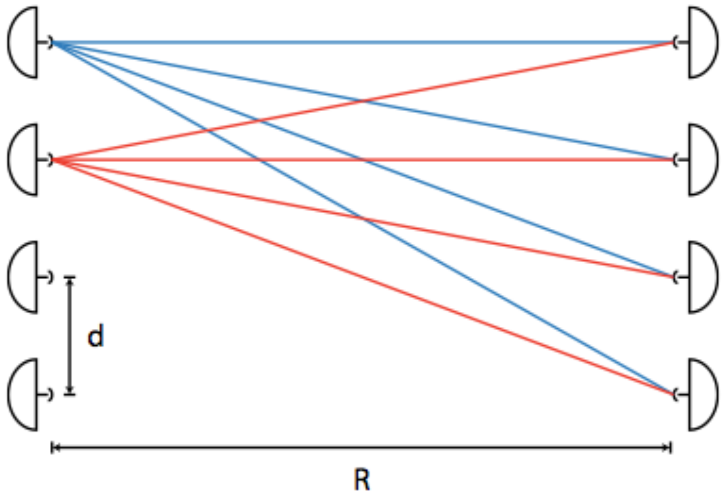
$$\frac{L_T^2}{\lambda R}|g_n|^2 \alpha_n(q) = \int_{-L_T/2}^{L_T/2} \frac{\sin 2\pi \frac{L_r}{2\lambda R}(q-q')}{\pi(q-q')} \alpha_n(q')dq'$$

Spatial prolate spheroids

$$|g_n|^2 \approx 0 \text{ for } n > \boxed{\frac{L_T L_R}{\lambda R}(1+\epsilon)}$$

Spatial bandwidth

Can utilize all degs of freedom with finite # antennas



$$\mathbf{h}_1 = (1, e^{j\phi}, e^{j2^2\phi}, \ldots, e^{j(N-1)^2\phi})^T$$

$$\mathbf{h}_2 = (e^{j\phi}, 1, e^{j\phi}, \ldots, e^{j(N-2)^2\phi})^T$$

$$|\langle \mathbf{h}_1, \mathbf{h}_2 \rangle| = \left| \frac{\sin(N\phi)}{\sin\phi} \right|$$

$$\text{Vectors are orthogonal when } N\phi = N\frac{\pi d^2}{\lambda R} = \pi$$

$$d = \sqrt{\frac{\lambda R}{N}}$$

Example

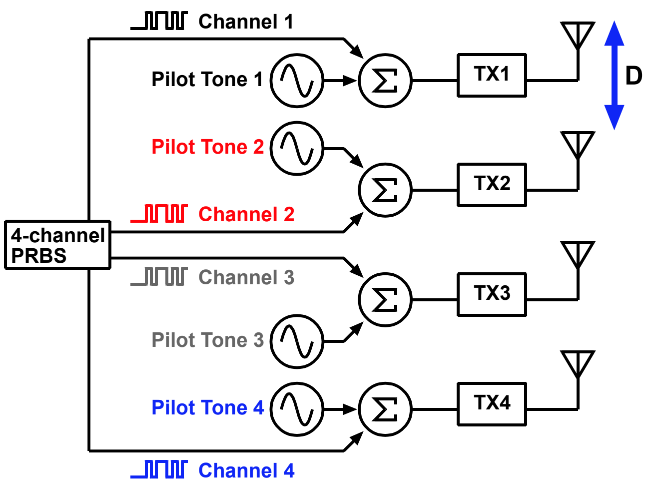
R=10 m, λ=5 mm, N=4

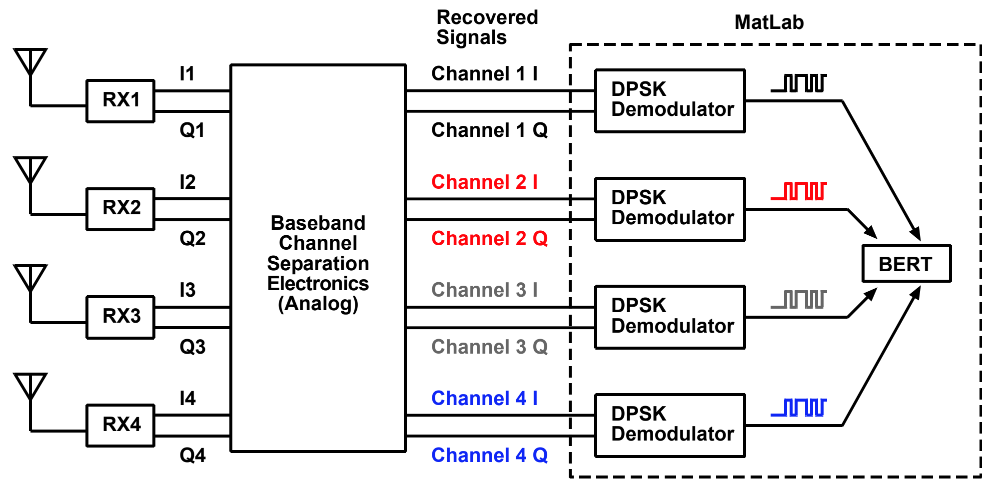
d =11 cm

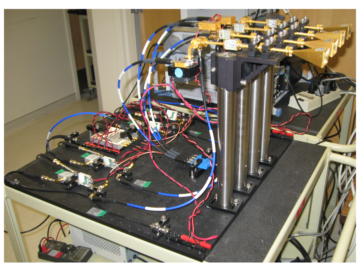
Torklidson, Madhow, Rodwell, IEEE Trans. Wireless Comm., Dec 2011.

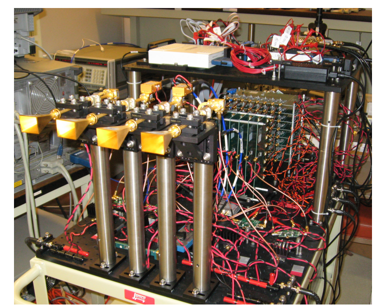
Demonstrating LoS MIMO: 4x4 Prototype

In collaboration with Prof. Mark Rodwell





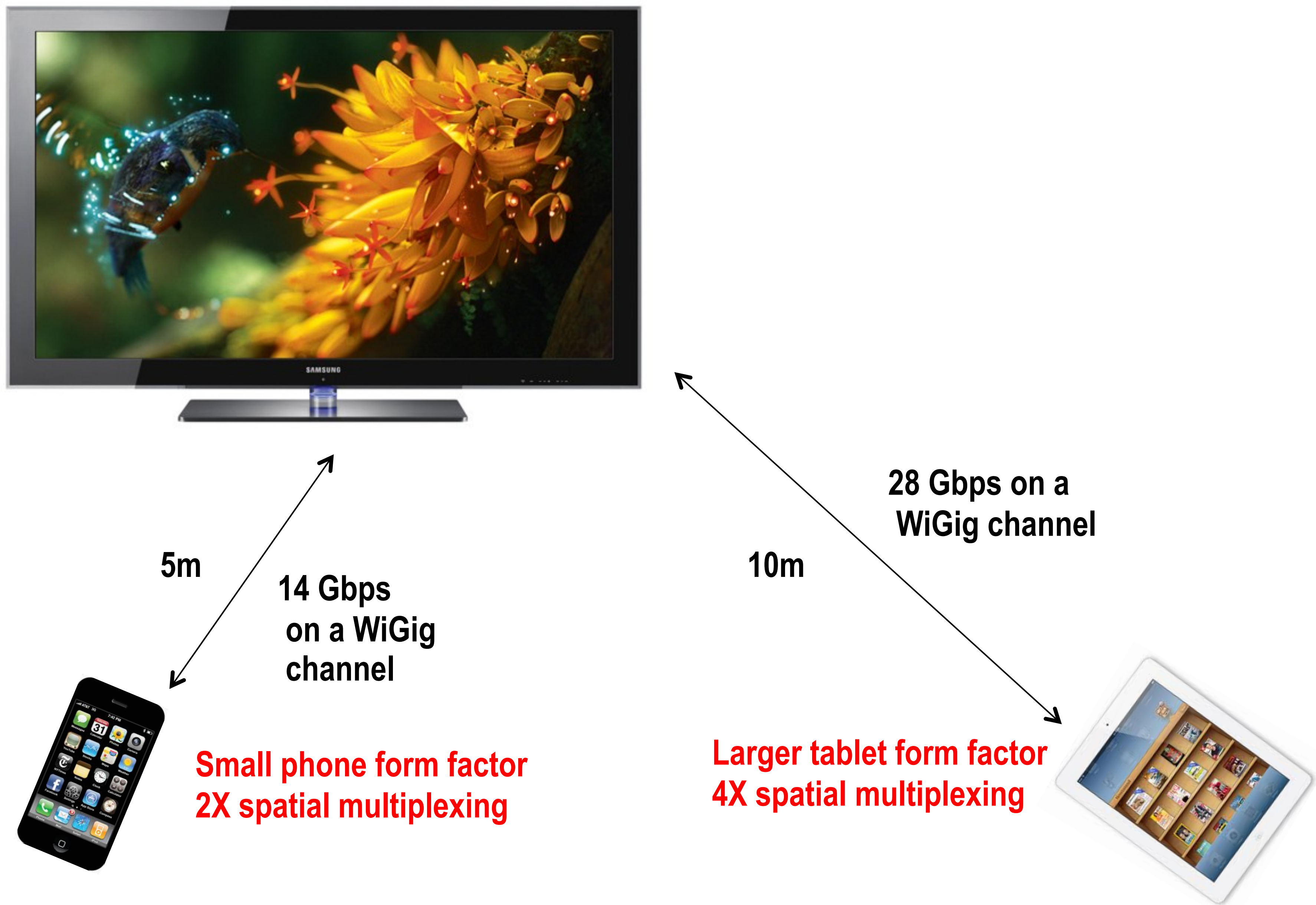




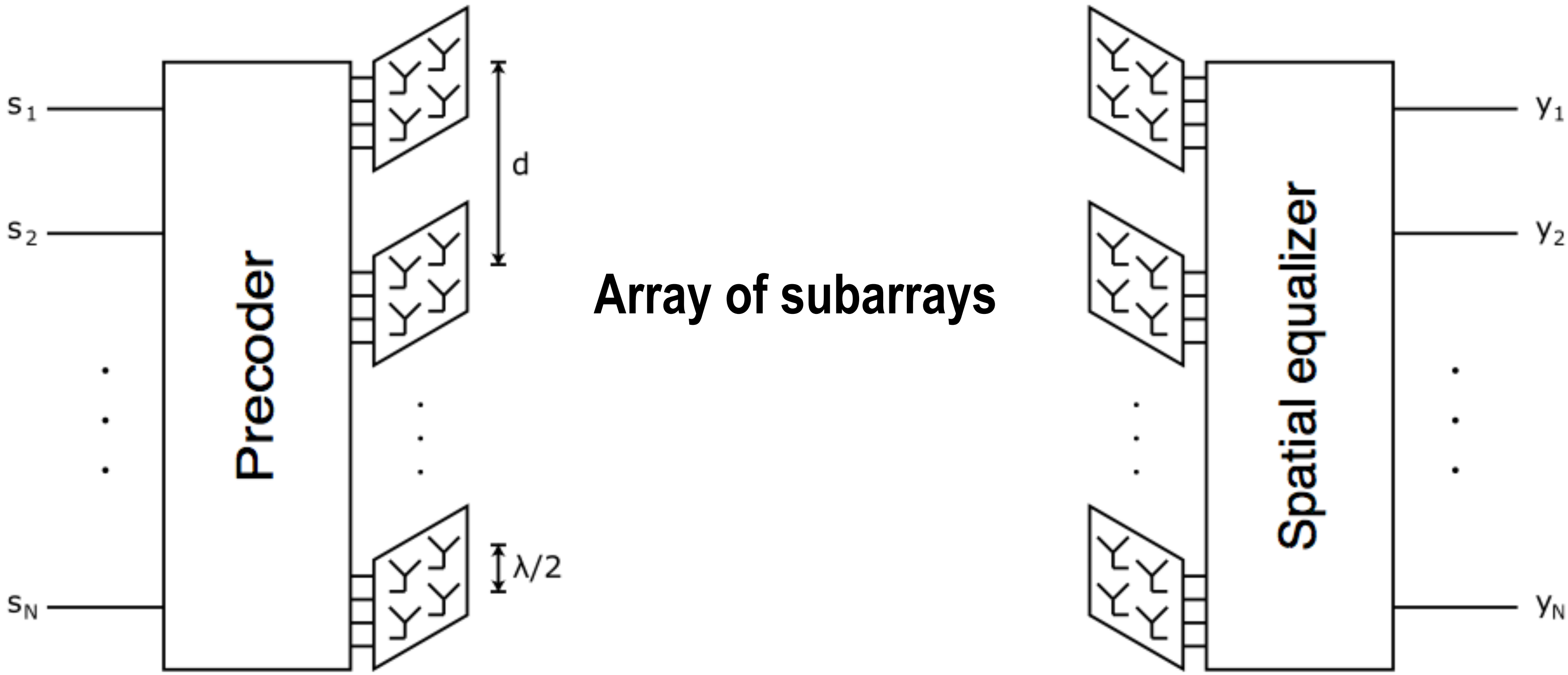
- **Embedded pilot tones used to identify channels at the receiver**
- **Decouple receiver functions: channel separation and data demodulation**
- **Channel separation network implemented with baseband analog circuits**

Sheldon et al, IEEE APSURSI 2010.

Spatial multiplexing for WiGig



Canonical architecture for mm wave MIMO

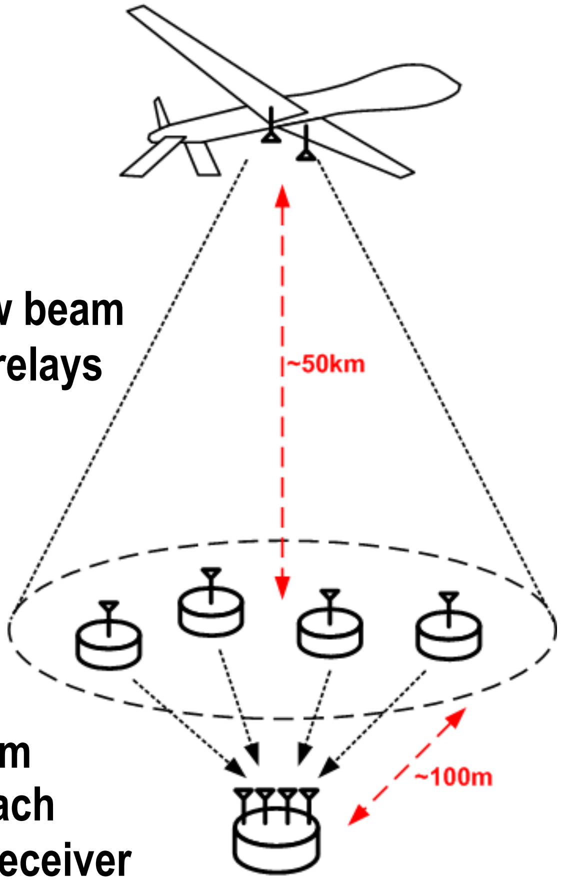


Rayleigh-spaced arrays: spatial multiplexing
(Smaller spacing: diversity)
Each array is a sub-wavelength spaced subarray: beamforming

RF beamforming per subarray. Mixed signal processing across.

Distributing subarrays to sidestep form factor constraints

The road to long-range wireless fiber: finally a compelling case for relays



Very narrow beam covers all relays

Moderately narrow beam between each relay and receiver

H_1 full-rank thanks to spatial spread of relays

H_2 diagonal => full-rank

Composite channel full-rank

Irish, Quitin, Madhow, ITA 2013

Signal processing for multi-GHz signals

How to scale system bandwidth indefinitely?

How to keep riding Moore's law?

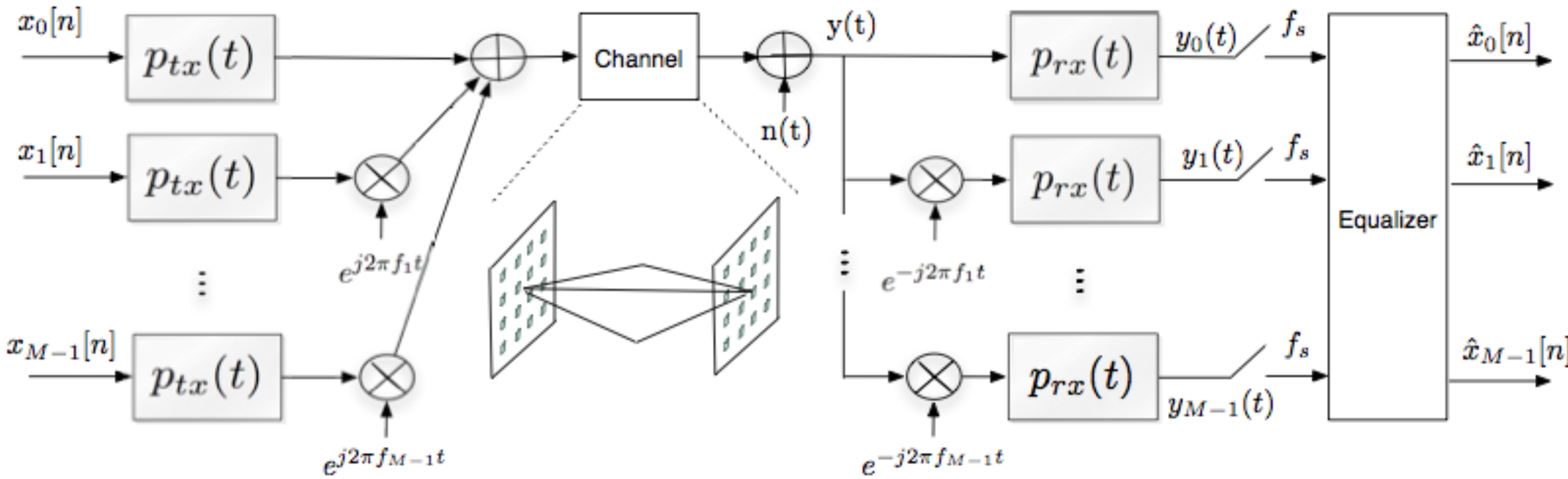
The bandwidth scaling problem

UCSB

- We like riding Moore's law
  - Enables economies of scale for cellular and WiFi
  - Keeps going at multiGigabit speeds
- The ADC is the bottleneck
  - High-rate, high-precision ADC costly, power-hungry and/or not available
  - Forces us beyond the OFDM comfort zone
- Clever solutions with low-precision ADC (1-4 bits)?
  - OK if we can keep dynamic range under control
- Time-interleaved ADCs?
  - Each sub-ADC still sees the full bandwidth

Is there a natural successor to OFDM as we scale bandwidth?

Analog Multitone for indefinite scalability

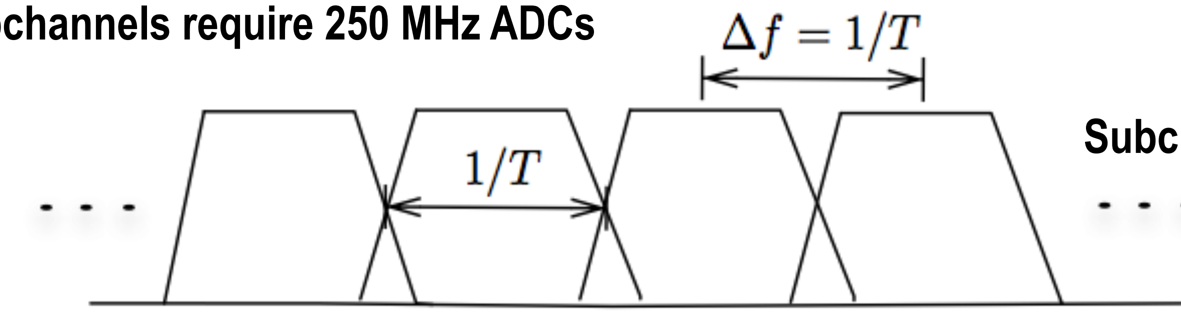


- Off-the-shelf ADC technology determines subchannel speed
- Desired bandwidth determines number of subchannels (much fewer than number of subcarriers in OFDM)
- Analog channelization at transmitter and receiver
- Sophisticated DSP for each subchannel: combat both ISI and ICI
- Promising simulation results for 1 x 2 60 GHz backhaul link

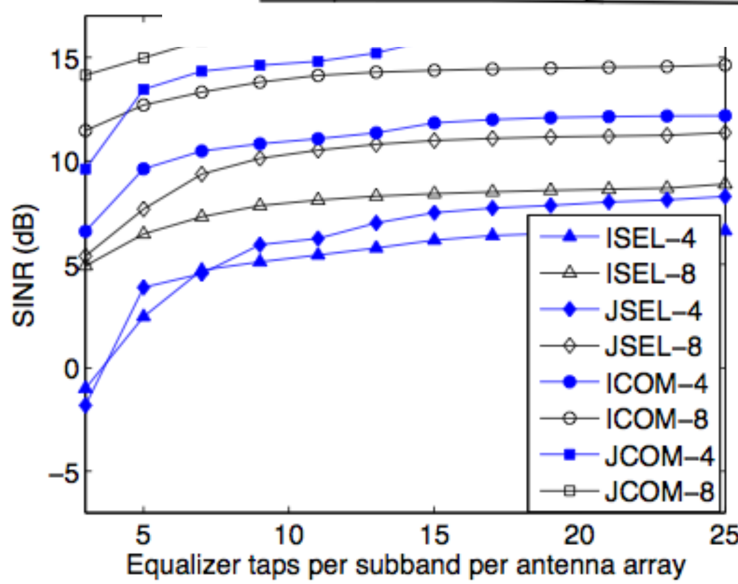
Zhang, Venkateswaran, Madhow, *Analog multitone with interference suppression: relieving the ADC bottleneck for wideband 60 GHz systems,* IEEE Globecom 2012.

Example: 60 GHz backhaul link

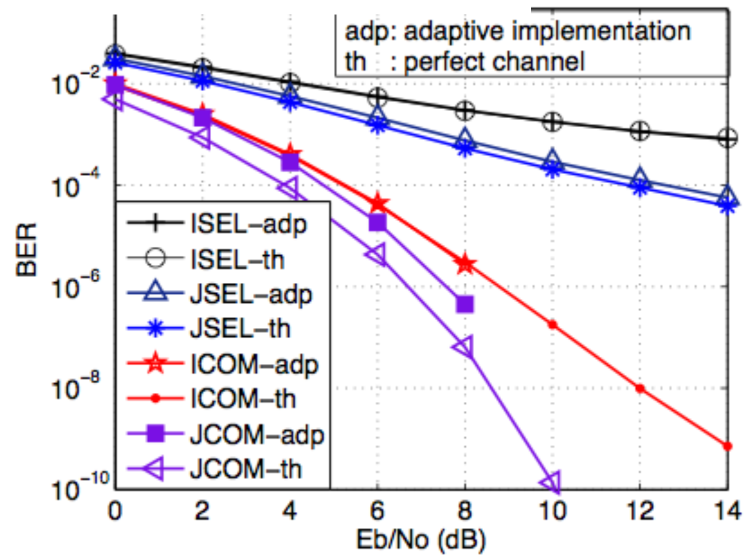
2 GHz bandwidth, 200 m range, two receive antenna arrays for five 9s diversity
4 subchannels require 500 MHz ADCs
8 subchannels require 250 MHz ADCs



Subchannels allowed to overlap



Small number of equalizer taps



No error floor if using two receive arrays

Currently exploring OFDM within subchannels for indoor settings

Parting thoughts on the mm wave frontier

- Getting the most out of 60 GHz indoors
  - Near-LoS MIMO, rapid beam adaptation, handling blockage
- Picocellular backhaul
  - Quasi-deterministic links, highly directional mesh networks
- Mm wave to the mobile
  - Electrically large arrays, rapid adaptation and tracking, network-level coordination
- Wireless data centers
  - 3D beamforming and near-LoS MIMO
- Long-range wireless fiber
  - Distributed architectures for sidestepping geometric constraints
- Signal processing at scale: addressing the ADC bottleneck head on

Significant interdisciplinary effort over the next 2 decades

SPAWC focus

- Array of subarrays as a canonical MIMO architecture
  - RF beamforming within subarray
  - Digital, or mixed analog-digital, signal processing across subarrays
- The ADC bottleneck
  - ADC-constrained but DSP-centric design for multiGHz systems
  - Analog multitone as the new OFDM?
- But SP cannot be practiced in a silo
  - Must account for the physics of tiny wavelengths
  - Must account for hardware constraints associated with scaling
  - Must interact with directional networking protocols

Exploring further

Survey

U. Madhow, S. Singh, *60 GHz communication,* chapter in *Handbook of Mobile Comm.* (ed. J. Gibson), 2012.

MIMO techniques and channel modeling

Sheldon, Seo, Torkildson, Madhow, Rodwell*, A 2.4 Gb/s millimeter-wave link using adaptive spatial multiplexing,* APS-URSI 2010.

Torkildson, Madhow, Rodwell, *Indoor millimeter wave MIMO: feasibility and performance,* IEEE Trans.Wireless Comm., Dec 2011. (see also mmCom 2010)

Zhang, Venkateswaran, Madhow, *Channel modeling and MIMO capacity for outdoor millimeter wave links,* WCNC 2010. (see also mmCom 2010)

Compressive adaptation

Ramasamy, Venkateswaran, Madhow, *Compressive adaptation of large steerable arrays* ITA 2012.

Ramasamy, Venkateswaran, Madhow, *Compressive tracking with 1000-element arrays…,* Allerton 2012.

Ramasamy, Venkateswaran, Madhow, *Compressive estimation in AWGN,* TSP, April 2014.

ADC Bottleneck

Zhang, Venkateswaran, Madhow, *Analog multitone with interference suppression: relieving the ADC bottleneck for wideband 60 GHz systems,* IEEE Globecom 2012.

Ponnuru, Seo, Madhow, Rodwell, *Joint mismatch and channel compensation for high-speed OFDM receivers with time-interleaved ADCs,* IEEE TCOM, August 2010.

Singh, Dabeer, Madhow, *On the limits of communication with low-precision analog-to-digital conversion at the receiver,* IEEE TCOM, December 2009.

Networking with highly directional links

Singh, Mudumbai, Madhow*, Interference analysis for highly directional 60-GHz mesh networks: the case for rethinking medium access control,* IEEE/ACM Trans. Networking, October 2011.

Singh, Mudumbai, Madhow, *Distributed coordination with deaf neighbors: efficient medium access for 60 GHz mesh networks,* IEEE Infocom 2010.

Singh, Ziliotto, Madhow, Belding, Rodwell, *Blockage and directivity in 60 GHz WPANs,* IEEE JSAC, October 2009.

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