Compressive tracking in mm wave picocells

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Network context

- Can fit very large arrays into picocell base stations
- Mobile users move ➔ agile tracking needed
- Beams are easily blocked, so must be able to switch
  - to alternate paths
  - to alternate base stations

Each base station must maintain a path inventory for each user
Cellular 1000X via mmwave picocells

- 10-100X bandwidth (2GHz vs. 20-200 MHz)
- 100X # antennas in same form factor ➔ pencil beams
  - Beamforming gain enables comm. over outdoor ranges
  - Reduced interference enables aggressive spatial reuse (100x)

32 x 32
8 x 8 cm^2

mmwave picocell architecture
Need to identify paths on the fly

• Blockage

• Motion tracking
Need hyper-efficient channel tracking

- To maintain a robust link despite mobility
- Overcome blockage
- Interference management to utilize spatial reuse
- Handover
How rapidly must we track?

How long before direction information expires?

- Speed of mobile user
- Width of beam

\[ W = r \theta \]

Pedestrian \( V = 5 \text{ m/s} \)  Update every 40ms
Vehicle \( V = 20 \text{ m/s} \)  Update every 10ms

\(< 1\text{ms} \) (desired)
Basic calculations

\[ W = r \theta \]

\[ \tau = \frac{W/2}{V \cos \alpha} \]

angle between speed and beam cross section

Tracking overhead?

Approximation under worst-case settings for N x N array

\[ \tau \approx \frac{0.888r}{Nv} \]

Need to update more frequently for larger arrays

Example: urban picocellular base station tracking a vehicle

\[ r = 5 \text{ m}, \quad v = 20 \text{ m/s}, \quad N = 16 \rightarrow \tau = 13.8 \text{ ms} \]
Example designs

- 4x4: Update every 40ms
- 16x16: Update every 10ms
- 32x32: Update every 5ms
Outline

• Motivation and Background
  – There is a huge capacity at mmwave band

• Path tracking is the key bottleneck
  – Shortcomings of conventional approaches
  – Compressive estimation a promising alternative

• Noncoherent compressive estimation
  – Works with off-the-shelf hardware

• Evaluation on 60 GHz testbed and simulations
Conventional direction finding techniques

• Exhaustive scanning
Conventional direction finding techniques

- Exhaustive scanning

Does not scale well with # of antennas (N)
Conventional direction finding techniques

- Hierarchical scanning:
  - Scales well with # of antenna (log(N))
  - Too much feedback overhead and delay
  - Does not scale well with # of users
  - Compromise on range and reliability
Compressive sensing: basic concept

Our framework: borrow the idea of pseudorandom projections for channel estimation
Mmwave channel model

High dimension (N)

Sparse (a few paths)
Compressive estimation

- Overhead (# of beacons) scales as Log(N)
- Scalable with # of users
- Each user sends only one feedback packet
- Support coarse phase control (e.g., 2bit)

\[ y_i = h_0 b_i^T a(\omega_0) + v_0 \]

#beacons scale logarithmically with #elements

- 1000 element array can be trained with only 24 beacons
- 5 μs per beacon

  training time < 120 μs

  overhead < 1.2 %  (once every 10 ms for fast car)
But today's transceivers can only do *Noncoherent* measurements

- Frequency offset between local oscillators at TX and RX
- Random phase offset in measurements

→ Phase of measurements cannot be used!

→ RSS-only measurements
Noncoherent compressive sensing

--Match (normalized) RSS measurements against expected RSS measurements across “spatial frequencies”
Hardware scalability: coarse phase control

- Large arrays, limited number of RF chains
- Simple RF phase control, for example via delay lines
  ➔ severe quantization of beamforming phases

Scanning requires fine-grained control
Compressive approaches work fine with severe phase quantization
EXPERIMENTS
Hardware: 60GHz testbed

• A pair of
  – 16x8 antenna array

Thanks: Facebook Terragraph team
Noncoherent cost function follows the same pattern as exhaustive scan.
Dominant path identified effectively

• **Single path**

![Graph showing spatial frequency error vs. number of beacons for single path.]

• **Two path** (one dominant path 8 dB stronger)

![Graph showing spatial frequency error vs. number of beacons for two path.]

- [2 bit]
- [4 bit]
Sims show effective scaling with array size
Compressive tracking take-aways

• Compressive channel tracking eliminates a key bottleneck to Cellular 1000X (and other mm-wave systems)
  – Low overhead
  – Scalable with # of users and # of antenna elements
  – Compatible with simplified hardware (heavily quantized phases)

• Noncoherent compressive estimation works with today’s hardware
  – Effective solution demonstrated when there is a single dominant path

• Recent result: noncoherent algorithms for multipath channels
Opens up new system design challenges

- Assuming each base station maintains path inventory for nearby mobile users
  - How do the base stations coordinate to provide robust connectivity?
  - How do the base stations coordinate to provide high throughput and manage interference?
  - How do we manage the transport layer?
  - What are the implications for backhaul requirements?
Appendix

Details of compressive scheme
Estimation problem

Channel is a sum of a few sinusoids

\[ h = g_1 x(\omega_1) + g_2 x(\omega_2) + g_3 x(\omega_3) \]

\[ x(\omega) = \begin{pmatrix} 1 \\ e^{j\omega} \\ e^{j2\omega} \\ \vdots \\ e^{j(N-1)\omega} \end{pmatrix} \]

\[ \omega_i = \frac{2\pi d}{\lambda} \sin \theta_i \]

Mobile makes compressive measurements

\[ y_i = a_i^T h, \; i = 1, 2, \ldots, M \]

Estimate gains and spatial frequencies from compressive measurements
Can we use standard compressed sensing?

\[ y = \sum_{k=1}^{L} g_k A x(\omega_k) + n \]
Basis mismatch is the problem

Frequencies come from a continuum, not a grid

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

Need compressive estimation in a continuum

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

• Acquisition
  – No knowledge of spatial frequencies whatsoever

• Tracking
  – Leverage frequency estimate from previous round
  – Refine based on new measurements
Acquisition: Coarse Estimate

\[
\text{maximize } F(\omega) = |\langle A x(\omega), y \rangle|^2 \\
\omega = 0, \frac{2\pi}{2N}, 2 \left( \frac{2\pi}{2N} \right), \ldots, (2N-1) \left( \frac{2\pi}{2N} \right)
\]
Acquisition: Coarse Estimate

maximize $F(\omega) = |\langle A x(\omega), y \rangle|^2$

\[ \hat{\omega}_1 = \frac{\langle A x(\hat{\omega}_1), y \rangle}{\|A x(\hat{\omega}_1)\|^2} \]
Iterative refinements

**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

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

\[ y_r = S^\perp y \]

**Coarsely estimate (K+1)th freq**

\[
\max_{\omega} \left| \langle A x(\omega), y_r \rangle \right|^2 \\
\omega = 0, \frac{2\pi}{2N}, 2 \left( \frac{2\pi}{2N} \right), \ldots, (2N - 1) \left( \frac{2\pi}{2N} \right) \\
\hat{\omega}_{K+1}, \hat{g}_{K+1}
\]

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

Stop when residual energy can be explained by noise: CFAR criterion
Simulation Setup

Array on lamp post
Within a dB of ideal beamforming

$8 \times 8$
The need for noncoherent tracking

• Phase synchronization not maintained between packets
  – Relative phase of measurements is corrupted
  – Coherent compressive estimation does not work

• Effective measurement model (high SNR approximation)

\[
y_i = |h_0 b_i^T x(\omega) + v_i|, \quad v_i \sim \mathcal{CN}(0, 2\sigma^2) \\
\approx |h_0 b_i^T x(\omega)| + v_i, \quad v_i \sim \mathcal{N}(0, \sigma^2)
\]
Noncoherent compressive tracking (single path)

- Noncoherent template matching gives ML estimate under high SNR approximation

\[ \hat{\omega}_0 = \arg \max_{\omega} J(\omega) \]

\[ J(\omega) = \left\langle \frac{y}{\|y\|}, \frac{|f(\omega)|}{\|f(\omega)\|} \right\rangle^2 \]
Noncoherent compressive tracking (single path)

coherent, 32 beacons

noncoherent, 32 beacons
What about multiple strong paths?

How do we sort out interference across paths?

\[ y_i \approx \left| \sum_{k=1}^{K} h_k b_i^T x(\omega_k) \right| + v_i, \quad v_i \sim \mathcal{N}(0, \sigma^2) \]
Recent result: Noncoherent can be made almost as efficient as coherent

Details omitted until publication
Experimental results not yet obtained
Time scale of tracking mobile user

\[ \tau = \frac{\Delta \theta_{3dB} r}{2v} \]
Time scale of tracking mobile user

3-dB beamwidth of $N$ element array:

Pattern of a 16 element array with $\lambda/2$ spacing

$$\theta_{3\text{dB}} \approx \frac{0.888}{N}$$
Time scale of tracking mobile user

3-dB beamwidth of N element array:

\[
\text{array response} = \left. \frac{\sin(N\pi/2 \sin \theta)}{N \sin(\pi/2 \sin \theta)} \right|_{\theta_{3dB}} = \frac{1}{\sqrt{2}}
\]

\[
\theta_{3dB} \approx \sin \theta_{3dB} = \alpha/N \Rightarrow \frac{\sin(\alpha\pi/2)}{N \sin(\alpha\pi/2N)} \approx \frac{1}{\sqrt{2}}
\]

\[
\approx \alpha\pi/2
\]

\[
\Rightarrow \alpha = 0.888, \quad \theta_{3dB} \approx \frac{0.888}{N} \quad (\Delta \theta_{3dB} \approx \frac{1.776}{N})
\]

\[
\tau = \frac{\Delta \theta_{3dB} r}{2\nu} \approx \frac{0.888 r}{N \nu}
\]