DISCRIMINATING AGAINST INTERFERENCE IN MASSIVE MIMO SYSTEMS: A STATISTICAL APPROACH

FUELING THE DENSE VS. MASSIVE DEBATE

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THE DIMENSIONS OF INTERFERENCE MANAGEMENT



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EXPLOITING AND COORDINATING INTERFERENCE

Transmitter cooperation involve substantial information sharing

- Coordination: transmitters exchange CSIT
 - Coordinated beamforming (CoMP in LTE-A), interference alignement, coordinated scheduling, coordinated power control..
- Exploitation: transmitters exchange CSIT and user data
 - Network (multicell) MIMO, Joint Processing CoMP
- **Rejection**: Simple per-terminal per-cell processing, little info exchange

Some questions:

- Are such methods scalable?
- Do distributed implementation exist?

EXPLOITING INTERFERENCE VIA MULTICELL MIMO



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THE "DENSE VS. MASSIVE" DEBATE

Dense cooperation (single antenna base station)



Massive MIMO base station (no cooperation)



WHAT CAN SIMPLE DISTRIBUTED BEAMFORMING ACHIEVE?



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- Let *M* antennas be used at BS 1 and BS 2.
- As $M \to \infty$ (normalized) useful and interference channel vector become quasi orthogonal
- Matched filter maximizes SNR and cancels interference simultaneously [Marzetta 2010]
- Matched filter solution is fully distributed!

But there is a problem...

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- Non orthogonal pilots -> pilot contamination (PC)
- PC destroys Massive MIMO theoretical benefits

Pilot sequence in *I*-th cell: $\mathbf{s}_{I} = \begin{bmatrix} s_{I1} & s_{I2} & \cdots & s_{I\tau} \end{bmatrix}^{T}$ the $M \times \tau$ signal at the target base station (with noise **N**) is

$$\mathbf{Y} = \sum_{l=1}^{L} \mathbf{h}_l \mathbf{s}_l^T + \mathbf{N}$$
(1)

Least Squares (LS) estimator with full pilot reuse:

$$\widehat{\mathbf{h}}_{1}^{\text{LS}} = \mathbf{h}_{1} + \sum_{l \neq 1}^{L} \mathbf{h}_{l} + \mathbf{N}\mathbf{s}^{*}/\tau$$
(2)

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A MORE POWERFUL ESTIMATOR (WELL KNOWN!)

$$\rho(\mathbf{h}|\mathbf{y}) = \frac{\exp\left(-\left(\mathbf{h}^{H}\mathbf{R}^{-1}\mathbf{h} + (\mathbf{y} - \mathbf{S}\mathbf{h})^{H}(\mathbf{y} - \mathbf{S}\mathbf{h})/\sigma_{n}^{2}\right)\right)}{AB}$$

where

$$\mathbf{R} \triangleq \operatorname{diag}(\mathbf{R}_1, \cdots, \mathbf{R}_L) \tag{3}$$

$$A \triangleq (\pi \sigma_n^2)^{M_{\tau}}$$
 and
 $B \triangleq \pi^{LM} (\det \mathbf{R})^M$ (4)

Develop covariance-based (Bayesian or MMSE) estimator

$$\widehat{\mathbf{h}}_{1} = \mathbf{R}_{1} \left(\sigma_{n}^{2} \mathbf{I}_{M} + \tau \sum_{l=1}^{L} \mathbf{R}_{l} \right)^{-1} \mathbf{S}^{H} \mathbf{y}$$
(5)

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 \mathbf{R}_{l} is covariance matrix of *l*-th interference channel.

Theorem [Yin, Gesbert, Filippou, Liu JSAC 2013] Assume multipath angle-of-arrival θ for user j (at target BS 1) has density $p_j(\theta)$ with bounded support, i.e. $p_j(\theta) = 0$ for $\theta \notin [\theta_j^{\min}, \theta_j^{\max}]$ for some fixed $\theta_j^{\min} \leqslant \theta_j^{\max} \in [0, \pi]$. If the L - 1intervals $[\theta_j^{\min}, \theta_i^{\max}]$, i = 2, ..., L are strictly non-overlappipng with $[\theta_1^{\min}, \theta_1^{\max}]$, we have

$$\lim_{M \to \infty} \widehat{\mathbf{h}}_1 = \widehat{\mathbf{h}}_1^{\text{no int}}$$
(6)

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If desired and interference multipath ranges do no overlap, pilot contamination vanish asymptotically.

LEARNING FROM CHANNEL MODELS

Classical specular channel model: $\mathbf{h}_i = \frac{1}{\sqrt{P}} \sum_{p=1}^{P} \mathbf{a}(\theta_{ip}) \alpha_{ip}$ where *P* is number of paths and

$$\mathbf{a}(heta) riangleq \left[egin{array}{c} \mathbf{1} \ e^{-j2\pirac{D}{\lambda}\cos(heta)} \ dots \ e^{-j2\pirac{(M-1)D}{\lambda}\cos(heta)} \end{array}
ight]$$

(7)

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Density function of random variable θ contains useful information, captured by correlation matrix.

$$\mathbf{R}_{\mathbf{i}} = \frac{\delta_i^2}{P} \sum_{p=1}^{P} \mathbb{E}\{\mathbf{a}(\theta_{ip})\mathbf{a}(\theta_{ip})^H\} = \delta_i^2 \mathbb{E}\{\mathbf{a}(\theta_i)\mathbf{a}(\theta_i)^H\}$$

Proof relies on three lemmas:

Lemma 1:

Define $\alpha(\mathbf{x}) \triangleq \begin{bmatrix} 1 & e^{-j\pi x} & \cdots & e^{-j\pi(M-1)x} \end{bmatrix}^T$. Given $b_1, b_2 \in [-1, 1]$ and $b_1 < b_2$, define $\mathcal{B} \triangleq \text{span}\{\alpha(\mathbf{x}) | \mathbf{x} \in [b_1, b_2]\}$, then

• dim{ \mathbb{B} } ~ $(b_2 - b_1)M/2$ when M grows large.

lemma 2 When M grows large,

 $\operatorname{rank}(\mathbf{R}_i) \leqslant d_i M$

where

$$m{d}_i riangleq \left(\cos(heta_i^{min}) - \cos(heta_i^{max})
ight) rac{m{D}}{\lambda}$$

Lemma 1 indicates that for large *M*, there exists a null space null(\mathbf{R}_i) of dimension $(1 - d_i)M$.

lemma 3 When M is large, the null space $null(\mathbf{R}_i)$ includes the following set of unit norm vectors:

$$\mathsf{null}(\mathbf{R}_i) \supset \mathsf{span}\left\{\frac{\mathbf{a}(\Phi)}{\sqrt{M}}, \forall \Phi \notin [\theta_i^{\mathsf{min}}, \theta_i^{\mathsf{max}}]\right\}$$

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LEARNING FROM COVARIANCE MATRICES



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DECONTAMINATING PILOTS PUT TO PRACTICE



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DECONTAMINATING PILOTS PUT TO PRACTICE

Coordinated Pilot Assignement (CPA):

- Estimate and exchange covariance information between cells (slow varying)
- Apply a coordinated pilot assignement based on covariance information to fulfill (almost) non-overlap condition between signal subspaces

A given pilot sequence is assigned to a user set ${\mathcal U}$ over L cells, minimizing a utility function

$$\mathsf{F}(\mathfrak{U}) \triangleq \sum_{j=1}^{|\mathfrak{U}|} \frac{\mathcal{M}_{j}(\mathfrak{U})}{\operatorname{tr} \{ \mathbf{R}_{jj}(\mathfrak{U}) \}}$$
(8)

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where $\mathcal{M}_{j}(\mathcal{U})$ is the MSE for the desired channel at the *j*-th base station

• Use a greedy approach to avoid exhaustive search

THE SKYSCRAPER EFFECT



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DECONTAMINATING PILOTS: PERFORMANCE

Angle spread 10 degrees



FIGURE: Estimation MSE vs. antenna number, Gaussian distributed AOAs with $\sigma = 10$ degrees.

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Discriminating against interference in Massive MIMO systems

DECONTAMINATING PILOTS: PERFORMANCE

10 Antennas



FIGURE: Per-cell sum-rate vs. standard deviation of AOA (Gaussian distribution) with M = 10, 7-cell network.

Uplink channel estimation with reused pilots:

$$\mathbf{Y} = \mathbf{h}_1 \mathbf{s}^T + \mathbf{h}_2 \mathbf{s}^T + \mathbf{N}, \tag{9}$$

Define the null space of \mathbf{R}_2 :

$$\mathbf{R}_{2} = \mathbf{U}\Sigma\mathbf{U}^{H} \quad \mathbf{W}_{1} = \left[\mathbf{u}_{m+1}|\mathbf{u}_{m+2}|\dots|\mathbf{u}_{M}\right]^{H}$$
(10)

Assume $h_1 \in \text{null space of } R_2$, then $h_1 = W_1^H \underline{h}_1$ where \underline{h}_1 is the effective channel. The subspace-based channel estimate is

$$\widehat{\mathbf{h}}_1 = \mathbf{W}_1^H \underline{\widehat{\mathbf{h}}}_1 = \mathbf{W}_1^H \mathbf{W}_1 \mathbf{Y} \mathbf{s}^* {(\mathbf{s}^T \mathbf{s}^*)}^{-1}$$
(11)

Note 1: One can also use the fact that $h_1 \in \text{signal subspace of } \mathbf{R}_2$.

Note 2: These properties can be exploited for feedback reduction in FDD context (Adhikary, Caire 2012).

PERFORMANCE OF SUBSPACE-BASED ESTIMATION

Angle spread 30 degrees+random scheduler \Rightarrow very poor performance!



FIGURE: Estimation MSE vs. antenna number, uniformly distributed AOAs with $\theta_{\Delta} = 30$ degrees, 2-cell network.

Is it really necessary to have a good channel estimate? No! Uplink received data:

$$\mathbf{y} = \mathbf{h}_1 \mathbf{s}_1^T + \mathbf{h}_2 \mathbf{s}_2^T + \mathbf{n}, \tag{12}$$

The subspace-based MRC beamformer is $\underline{\widehat{\boldsymbol{h}}}_1^H \boldsymbol{W}_1$

$$\underline{\widehat{\mathbf{h}}}_{1}^{H}\mathbf{W}_{1}\mathbf{y} = \underline{\widehat{\mathbf{h}}}_{1}^{H}\underline{\mathbf{h}}_{1}\mathbf{s}_{1}^{T} + \underbrace{\underline{\widehat{\mathbf{h}}}_{1}^{H}\mathbf{W}_{1}\mathbf{h}_{2}\mathbf{s}_{2}^{T}}_{\approx \mathbf{0}} + \underline{\widehat{\mathbf{h}}}_{1}^{H}\mathbf{W}_{1}\mathbf{n}$$
(13)

Subspace-based massive-MIMO beamformer yields good interference reduction signal enhancement trade-off...

SUBSPACE-BASED MRC BF: PERFORMANCE

Angle spread 30 degrees. Worst channel estimate yields best data rate!



FIGURE: Per-cell rate vs. antenna number, uniformly distributed AOAs with $\theta_{\Delta} = 30$ degrees, 2-cell network.

- Massive MIMO leads to strongly subspace structured covariances
- subspace orthogonality can be exploited for pilot decontamination, beamforming design, feedback reduction
- Orthogonality can be boosted with the help of coordinated pilot assignement and user scheduling
- Open issues: estimation of covariance matrices, random antenna arrays, dealing with skyscraper effects ...