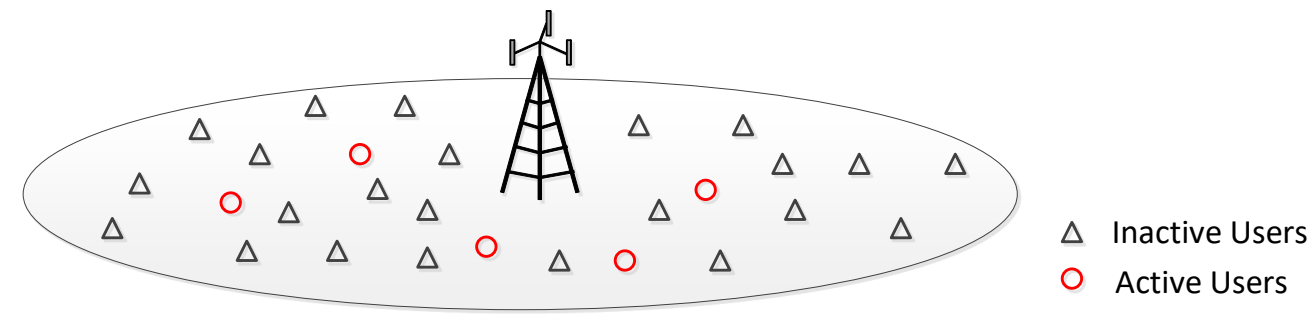




Sparse Activity Detection in Multi-Cell Massive MIMO Exploiting Channel Large-Scale Fading

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1. Massive Random Access



- A large number of devices with sporadic activity
- Non-orthogonal signature sequences for all the users
- User activity detection performed at base station (BS)

2. System Model

- BS equipped with M antennas
- N single-antenna devices, K of which are active at a time
- Each device is assigned a length- L unique signature \mathbf{s}_n
- Channel \mathbf{h}_n includes both Rayleigh and large-scale fading
- For **single-cell** system, received signal $\mathbf{Y} \in \mathbb{C}^{L \times M}$ at the BS is

$$\mathbf{Y} = \sum_{n=1}^N \alpha_n \mathbf{s}_n \mathbf{h}_n^T + \mathbf{Z} = \mathbf{S} \mathbf{X} + \mathbf{Z}, \quad (1)$$

- $\alpha_n \in \{1, 0\}$ activity indicator;
- $\mathbf{S} \triangleq [\mathbf{s}_1, \dots, \mathbf{s}_N] \in \mathbb{C}^{L \times N}$; $\mathbf{X} \triangleq [\alpha_1 \mathbf{h}_1, \dots, \alpha_N \mathbf{h}_N]^T \in \mathbb{C}^{N \times M}$

3. Joint Activity and Large-Scale Fading Estimation

Assumption: We only need activity α_n and do not need \mathbf{h}_n .

Recast as a large-scale-fading estimation problem:

$$\mathbf{Y} = \sum_{n=1}^N \alpha_n \mathbf{s}_n \mathbf{h}_n^T + \mathbf{Z} \triangleq \mathbf{S} \mathbf{\Gamma} \tilde{\mathbf{H}} + \mathbf{Z} \quad (2)$$

where $\mathbf{\Gamma} \triangleq \text{diag}\{\alpha_1 \beta_1, \alpha_2 \beta_2, \dots, \alpha_N \beta_N\} \in \mathbb{R}^{N \times N}$.

The **maximum likelihood estimation** of $\mathbf{\Gamma}$ can be formulated as

$$\begin{aligned} \min_{\mathbf{\Gamma} \geq 0} -\log p(\mathbf{Y}|\mathbf{\Gamma}) &\propto \min_{\mathbf{\Gamma} \geq 0} -\frac{1}{M} \sum_{m=1}^M \left(\log \frac{1}{|\pi \mathbf{\Sigma}|} \exp \left(-\mathbf{y}_m^H \mathbf{\Sigma}^{-1} \mathbf{y}_m \right) \right) \\ &= \min_{\mathbf{\Gamma} \geq 0} \log |\mathbf{\Sigma}| + \text{tr} \left(\mathbf{\Sigma}^{-1} \hat{\mathbf{\Sigma}} \right) + \text{const.} \\ &= \min_{\mathbf{\Gamma} \geq 0} \log |\mathbf{S} \mathbf{\Gamma} \mathbf{S}^H + \sigma^2 \mathbf{I}| + \text{tr} \left((\mathbf{S} \mathbf{\Gamma} \mathbf{S}^H + \sigma^2 \mathbf{I})^{-1} \hat{\mathbf{\Sigma}} \right) \end{aligned} \quad (3)$$

for which the sample covariance matrix is a sufficient statistics

$$\hat{\mathbf{\Sigma}} \triangleq \frac{1}{M} \sum_{m=1}^M \mathbf{y}_m \mathbf{y}_m^H = \frac{1}{M} \mathbf{Y} \mathbf{Y}^H. \quad (4)$$

This problem can be solved efficiently using coordinate descent.

4. Covariance Based Sparse Activity Detection

For the channel model:

$$\begin{bmatrix} L \\ M \end{bmatrix} = \begin{bmatrix} L \\ N \end{bmatrix} + \begin{bmatrix} L \\ M \end{bmatrix}$$

We now estimate large-scale fading $\mathbf{\Gamma}$ based on $\hat{\mathbf{\Sigma}} = \frac{1}{M} \mathbf{Y} \mathbf{Y}^H$:

$$\begin{aligned} \begin{bmatrix} L \\ M \end{bmatrix} \times \begin{bmatrix} L \\ M \end{bmatrix} &= \begin{bmatrix} L \\ N \end{bmatrix} \times \begin{bmatrix} L \\ M \end{bmatrix} + \begin{bmatrix} L \\ M \end{bmatrix} \\ \downarrow M \rightarrow \infty &\quad \downarrow \\ \begin{bmatrix} L \\ L \end{bmatrix} &= \begin{bmatrix} L \\ N \end{bmatrix} + \begin{bmatrix} L \\ M \end{bmatrix} \end{aligned}$$

Advantage: Instead of detecting KM variables based on LM observations, we now detect K variables based on L^2 observations!

5. Analysis of Maximum Likelihood Estimation

Theorem 1. Consider a single-cell sparse user activity detection problem. Let \mathcal{I} be the index set corresponding to inactive users, i.e., $\mathcal{I} \triangleq \{i \mid \gamma_i^0 = 0\}$. Define two sets \mathcal{N}, \mathcal{C} in \mathbb{R}^N as follows:

$$\mathcal{N} \triangleq \{\mathbf{x} \mid \mathbf{x}^T \mathbf{J}(\gamma^0) \mathbf{x} = 0, \mathbf{x} \in \mathbb{R}^N\}, \quad (5)$$

$$\mathcal{C} \triangleq \{\mathbf{x} \mid x_i \geq 0, i \in \mathcal{I}, \mathbf{x} \in \mathbb{R}^N\}, \quad (6)$$

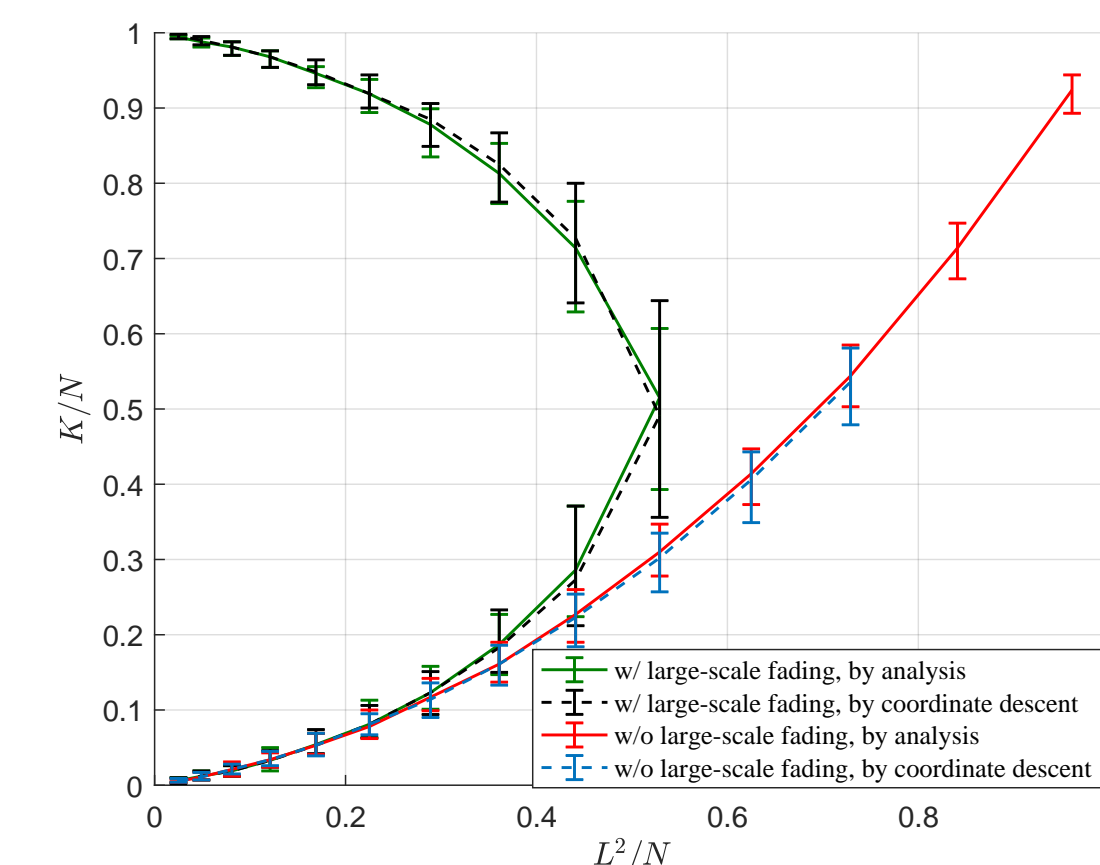
where x_i is the i -th entry of \mathbf{x} , and $\mathbf{J}(\gamma^0)$ is the Fisher information matrix. Then a necessary and sufficient condition for the consistency of $\hat{\gamma}^{ML}$, i.e., $\hat{\gamma}^{ML} \rightarrow \gamma^0$ as $M \rightarrow \infty$, is $\mathcal{N} \cap \mathcal{C} = \{0\}$.

Theorem 2. Suppose that large-scale fading β_n is known, for estimating the activity indicator $\alpha_n \in [0, 1]$ in $\gamma_n = \alpha_n \beta_n$, we define

$$\mathcal{N}' \triangleq \{\mathbf{x} \mid \mathbf{x}^T \mathbf{J}(\gamma^0) \mathbf{x} = 0, \mathbf{x} \in \mathbb{R}^N\}, \quad (7)$$

$$\mathcal{C}' \triangleq \{\mathbf{x} \mid x_i \geq 0, i \in \mathcal{I}, x_i \leq 0, i \notin \mathcal{I}, \mathbf{x} \in \mathbb{R}^N\}, \quad (8)$$

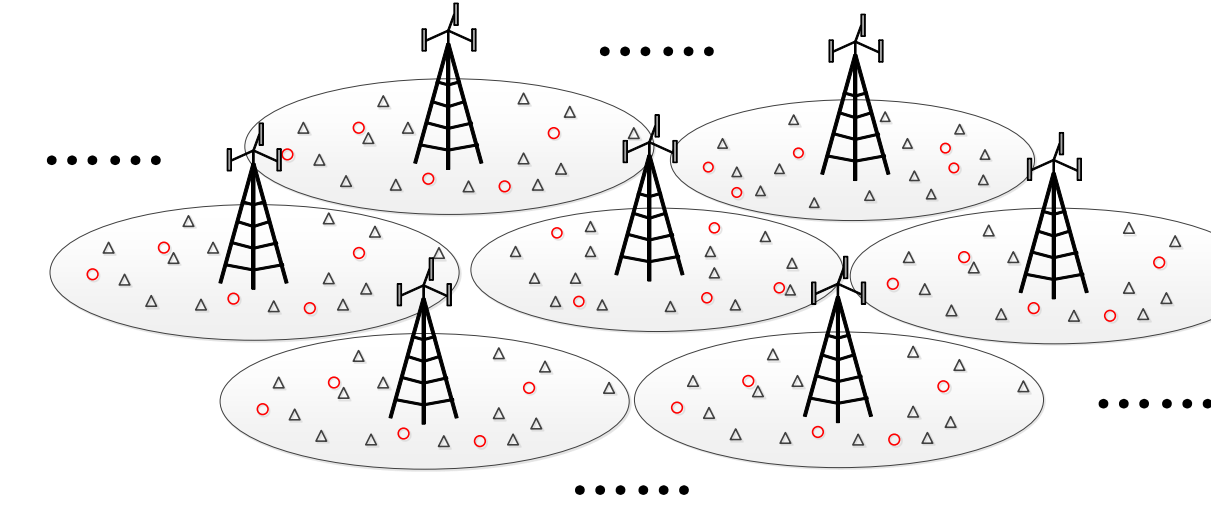
then a necessary and sufficient condition for the consistency of $\hat{\alpha}^{ML}$, i.e., $\hat{\alpha}^{ML} \rightarrow \alpha^0$ as $M \rightarrow \infty$, is $\mathcal{N}' \cap \mathcal{C}' = \{0\}$.



When $\frac{K}{N} \approx 1$, then inactive users are sparse!

6. Cooperative Activity Detection in Multicell Systems

- Multi-cell system with B BSs each equipped with M antennas;



- Received signal $\mathbf{Y}_b \in \mathbb{C}^{L \times M}$ at BS b is

$$\begin{aligned} \mathbf{Y}_b &= \sum_{n=1}^N \alpha_{bn} \mathbf{s}_{bn} \mathbf{h}_{bb}^T + \sum_{j=1, j \neq b}^B \sum_{n=1}^N \alpha_{jn} \mathbf{s}_{jn} \mathbf{h}_{bj}^T + \mathbf{Z}_b \\ &= \mathbf{S}_b \mathbf{A}_b \mathbf{G}_{bb}^{\frac{1}{2}} \tilde{\mathbf{H}}_{bb} + \sum_{j=1, j \neq b}^B \mathbf{S}_j \mathbf{A}_j \mathbf{G}_{bj}^{\frac{1}{2}} \tilde{\mathbf{H}}_{bj} + \mathbf{Z}_b \\ &= \mathbf{S}_b \mathbf{\Gamma}_{bb}^{\frac{1}{2}} \tilde{\mathbf{H}}_{bb} + \sum_{j=1, j \neq b}^B \mathbf{S}_j \mathbf{\Gamma}_{bj}^{\frac{1}{2}} \tilde{\mathbf{H}}_{bj} + \mathbf{Z}_b \end{aligned} \quad (9)$$

where $\alpha_{bm} \in \{1, 0\}$ is the activity indicator.

Cooperative detection: To alleviate the impact of inter-cell interference, we consider a BS cooperation architecture by assuming that all BSs are connected to a central unit, where all received signals are jointly processed.

- When \mathbf{G}_{bj} are unknown, we need to estimate $\mathbf{\Gamma}_{bj} = \mathbf{A}_j \mathbf{G}_{bj}$:

$$B^2 N \text{ unknown parameters}$$

- When \mathbf{G}_{bj} are known, we only need to estimate \mathbf{A}_b with

$$BN \text{ unknown parameters}$$

Theorem 3. Consider the problem of maximum likelihood estimation of user activities in a **multicell cooperative** system assuming **known large-scale fading**:

$$\min_{\{\mathbf{A}_b\}} \sum_{b=1}^B \left(\log |\mathbf{\Sigma}_b| + \text{tr} \left(\mathbf{\Sigma}_b^{-1} \hat{\mathbf{\Sigma}}_b \right) \right) \quad (10a)$$

$$\text{s. t. } \alpha_{bn} \in \{0, 1\}, \forall b, n. \quad (10b)$$

Let $\underline{\alpha} \triangleq [\alpha_1, \dots, \alpha_{BN}]^T$ be the activity indicators, and let true value of $\underline{\alpha}$ be $\underline{\alpha}^0$. Let \mathcal{I} be index set corresponding to zero entries of $\underline{\alpha}^0$, i.e., $\mathcal{I} \triangleq \{i \mid \alpha_i^0 = 0\}$. We define two sets $\mathcal{N}'', \mathcal{C}''$ in the space \mathbb{R}^{BN} , respectively, as follows

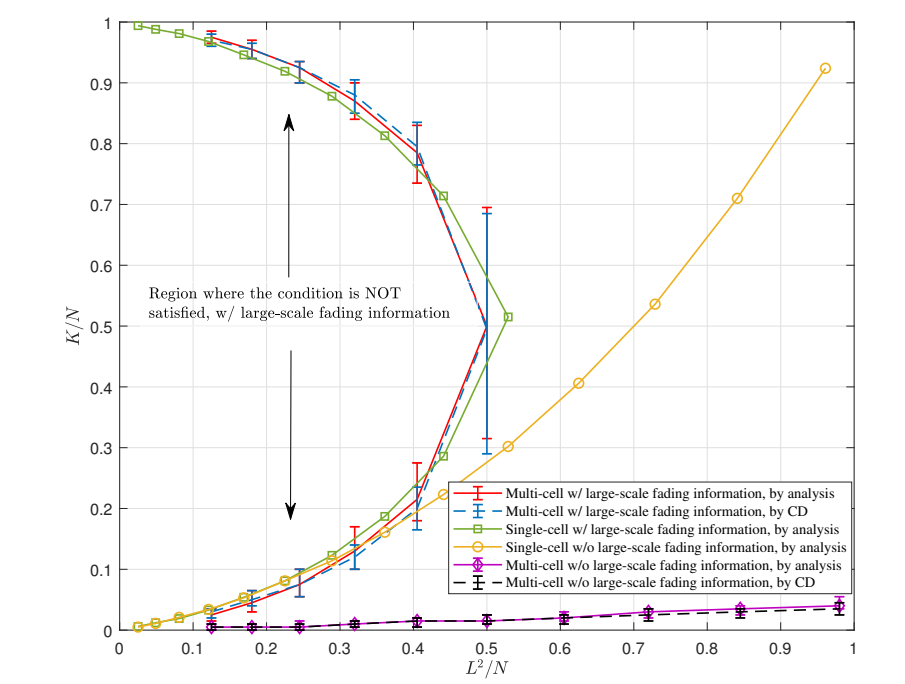
$$\mathcal{N}'' \triangleq \{\mathbf{x} \mid \mathbf{x}^T \mathbf{J}(\gamma^0) \mathbf{x} = 0, \mathbf{x} \in \mathbb{R}^{BN}\}, \quad (11)$$

$$\mathcal{C}'' \triangleq \{\mathbf{x} \mid x_i \geq 0, i \in \mathcal{I}, x_i \leq 0, i \notin \mathcal{I}, \mathbf{x} \in \mathbb{R}^{BN}\}, \quad (12)$$

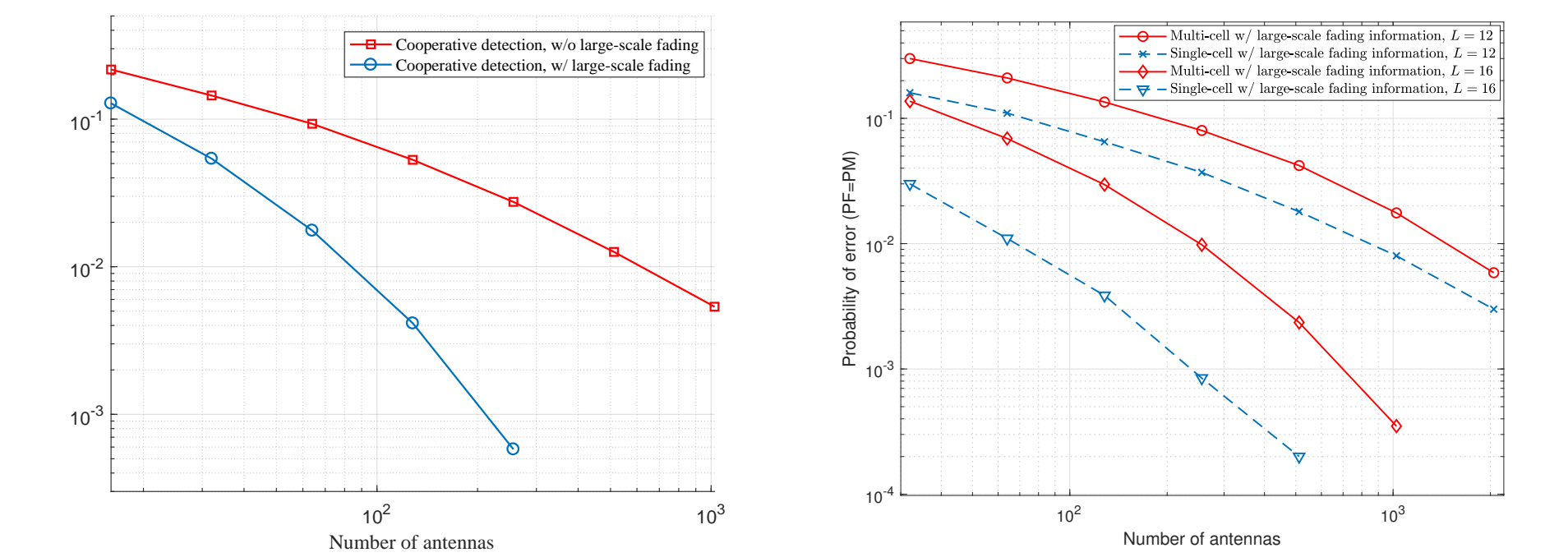
where x_i is the i -th entry of \mathbf{x} . Then a necessary and sufficient condition for the consistency of $\hat{\underline{\alpha}}^{ML}$, i.e., $\hat{\underline{\alpha}}^{ML} \rightarrow \underline{\alpha}^0$ as $M \rightarrow \infty$, is $\mathcal{N}'' \cap \mathcal{C}'' = \{0\}$.

7. Sparse Activity Detection: Multicell vs. Single-Cell

With cooperation and assuming known large-scale fading, all dimensions of the problem scale by B , so we expect **phase transition to be the same!** For example, for $B = 7$, $N = 200$:



Practical detection performance: $B = 7$, $N = 200$, $K = 20$, $L = 20$



8. Conclusions

- Device activity detection for massive random access is a sparse recovery problem.
- This paper extends the analysis and algorithm for covariance based MLE of device activity detection to multicell systems.
- Multicell cooperative detection has a similar phase transition as single-cell system, **but only if large-scale fading is known.**
- In practice, there is significant performance degradation due to intercell interference.

References

- [1] A. Fengler, S. Haghighatshoar, P. Jung, and G. Caire, "Non-Bayesian Activity Detection, Large-Scale Fading Coefficient Estimation, and Unsourced Random Access with a Massive MIMO Receiver", *IEEE Trans. Inf. Th.*, May 2021.
- [2] Zhilin Chen, Foad Sohrabi, Ya-Feng Liu, Wei Yu, "Phase Transition Analysis for Covariance Based Massive Random Access with Massive MIMO", Submitted to *IEEE Trans. Inf. Th.*, March 2020. [Online] <https://arxiv.org/abs/2003.04175>
- [3] Zhilin Chen, Foad Sohrabi, and Wei Yu, "Sparse Activity Detection in Multi-Cell Massive MIMO Exploiting Channel Large-Scale Fading", *IEEE Trans. Signal Processing*, June 2021.