

Near-Field Sensing and Communications with Reconfigurable Antennas

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- ① Introduction
- ② Near-Field S&C with Power Sensors at Antennas
 - Power Sensor-Enabled Localization
 - Power Sensor-Enhanced Channel Estimation
- ③ Near-Field Communications with Movable Antennas
 - A Functional Perspective
 - A Discrete Approach
- ④ Conclusion

Outline

- 1 **Introduction**
- 2 Near-Field S&C with Power Sensors at Antennas
 - Power Sensor-Enabled Localization
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- 3 Near-Field Communications with Movable Antennas
 - A Functional Perspective
 - A Discrete Approach
- 4 **Conclusion**

Introduction

- Every leap in wireless systems from 2G to 5G has been propelled by relentless advancements in antenna technology

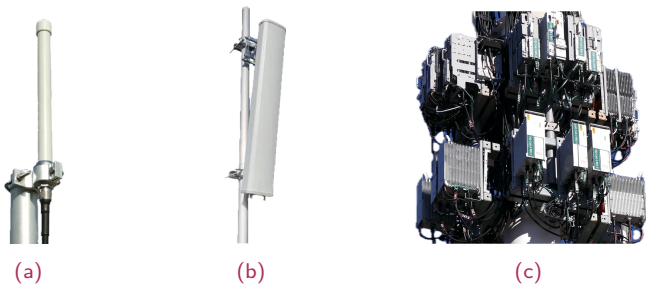


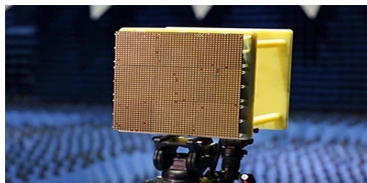
Figure 1: (a) Omnidirectional single antenna, (b) Sectorized array, (c) Multi-beam station

Introduction

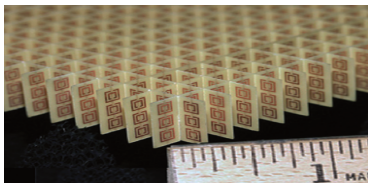
■ **XL-MIMO** antenna arrays widely investigated in beyond 5G systems



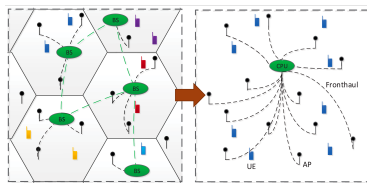
(a) Massive MIMO BS



(b) Reconfigurable Intelligent Surface



(c) Holographic MIMO



(d) Cell-free mMIMO

Figure 2: Widely investigated XL-MIMO related topics.

Introduction

- **XL-MIMO** with large aperture and massive elements **expands the near-field (NF) region**

- Near-field region, a.k.a., **Fresnel region**, is bounded as

$$\sqrt[3]{\frac{2D^4}{\lambda}} \leq d_{\text{NF}} \leq \frac{2D^2}{\lambda}, \quad D \blacktriangle \lambda \blacktriangledown \Rightarrow d_{\text{NF}} \blacktriangle$$

- A 50 m distance already falls in the NF region of a 64-element array operating at centimetre wave $f_c = 10$ GHz

Introduction

- Near-field region, a.k.a., **Fresnel region**, expands significantly

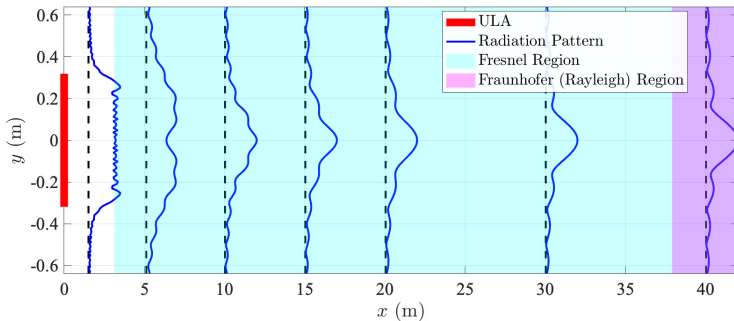


Figure 3: Radiation Pattern at different distances.

- Determined not only by **Angle θ** but also by **Distance r**

Introduction

- In the **near-field** region, EM wavefront is not planar, but **spherical**

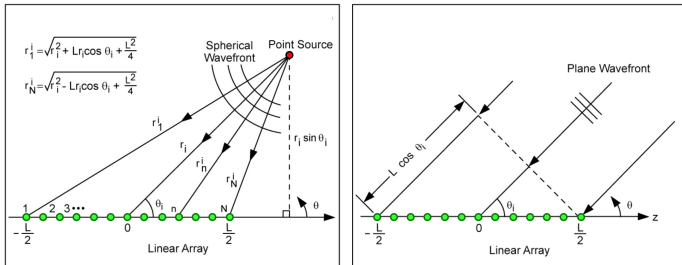


Figure 4: Wavefront illustration [1].

- Spatial (channel) response:

$$g(\mathbf{r}_{\text{BS}}^{(n)}, \mathbf{r}_{\text{UE}}^{(m)}) = e^{-j\kappa \sqrt{\|\mathbf{r}_{\text{BS}}^{(n)}\|^2 + \|\mathbf{r}_{\text{UE}}^{(m)}\|^2 - 2\|\mathbf{r}_{\text{BS}}^{(n)}\| \|\mathbf{r}_{\text{UE}}^{(m)}\| \cos(\vartheta_{m,n})}}$$

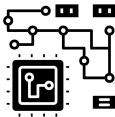
- [1] A. Fenn, "Evaluation of adaptive phased array antenna, far-field nulling performance in the near-field region," *IEEE Trans. Antennas Propag.*, vol. 38, no. 2, pp. 173–185, 1990.

Challenges in Near-Field Sensing & Communications

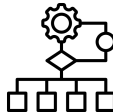
- Two degrees of freedoms (r, θ) in NF channels
- Sensing/channel estimation
 - ▶ More parameters to be estimated
 - ▶ A large number of **high-speed ADCs** for baseband sampling
 - ▶ Polynomially increasing **computational complexity**

Challenges in Near-Field Sensing & Communications

- Two degrees of freedoms (r, θ) in NF channels
- Sensing/channel estimation
 - ▶ More parameters to be estimated
 - ▶ A large number of **high-speed ADCs** for baseband sampling
 - ▶ Polynomially increasing **computational complexity**
- Communications
 - ▶ Conventional **uniform** array geometry cannot effectively capture the **non-uniform** spatial variation in the NF spherical wavefront
 - ▶ Lack of **customized** design methodologies for NF communications



Hardware



Algorithm

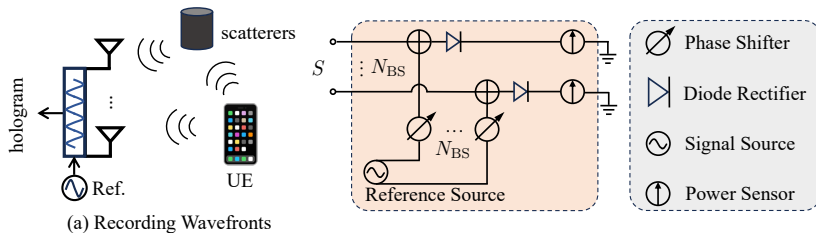
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Power Sensor-Enabled Localization: Recording

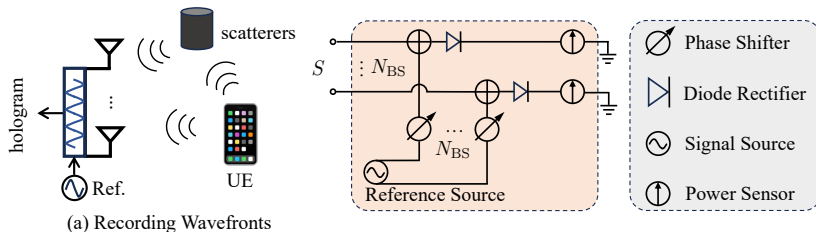


Received signal at the n -th antenna element of the BS, $\mathbf{e}_{\text{obj}}[n]$, carrying the NF channel information $g(\mathbf{r}_{\text{BS}}^{(n)}, \mathbf{r}_{\text{UE}})$

Antennas elements record the power

$$\begin{aligned}
 p[n] &= |\mathbf{e}_{\text{ref}}[n] + \mathbf{e}_{\text{obj}}[n]|^2 \\
 &= |\mathbf{e}_{\text{ref}}[n]|^2 + |\mathbf{e}_{\text{obj}}[n]|^2 + \underbrace{\mathbf{e}_{\text{ref}}^*[n]\mathbf{e}_{\text{obj}}[n] + \mathbf{e}_{\text{ref}}[n]\mathbf{e}_{\text{obj}}^*[n]}_{\text{Desired}},
 \end{aligned}$$

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 \end{aligned}$$

Power Sensor-Enabled Localization: Reconstruction I

- Remove the undesired signals, build **hologram**

$$\begin{aligned} \mathbf{p}[n] - |\mathbf{e}_{\text{ref}}[n]|^2 &\gtrsim \underbrace{\mathbf{e}_{\text{ref}}^*[n]\mathbf{e}_{\text{obj}}[n]}_{\text{Desired}} + \mathbf{e}_{\text{ref}}[n]\mathbf{e}_{\text{obj}}^*[n] \\ &\triangleq \mathbf{h}[n], \end{aligned}$$

- Recover the phase information of $\mathbf{e}_{\text{obj}}[n]$

$$\bar{\mathbf{h}}[n] = \mathbf{h}[n]\mathbf{e}_{\text{ref}}[n]$$

- Construct a field $\tilde{E}(\mathbf{r})$ by emulating Back-Projection of EM wave from BS to any location $\mathbf{r}$

$$\tilde{E}(\mathbf{r}) = \sum_{n=1}^{N_{\text{BS}}} \bar{\mathbf{h}}[n] \|\mathbf{r} - \mathbf{r}_{\text{BS}}^{(n)}\| g^* \left(\mathbf{r}_{\text{BS}}^{(n)}, \mathbf{r} \right)$$

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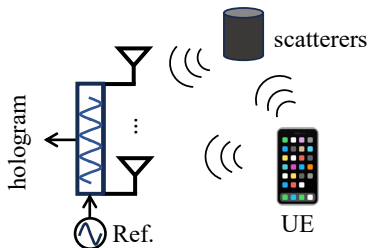
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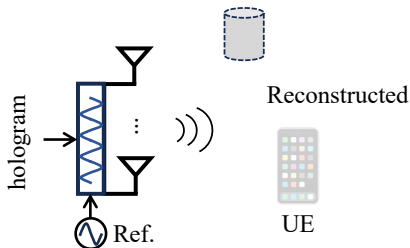
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Power Sensor-Enabled Localization: Reconstruction II

■ Back projection/Time inversion localization algorithm



(a) Recording Wavefronts



(b) Emulate Wavefront Back-projection

- $\mathbf{e}_{\text{obj}}[n]$: Generated by the **forward** propagation $g\left(\mathbf{r}_{\text{BS}}^{(n)}, \mathbf{r}\right)$
- $\tilde{E}(\mathbf{r})$: **Back-project** the processed $\mathbf{e}_{\text{obj}}[n]$ via $g^*\left(\mathbf{r}_{\text{BS}}^{(n)}, \mathbf{r}\right)$

Power Sensor-Enabled Localization: Reconstruction III

- The reconstructed object wave consists of THREE parts

$$\begin{aligned}\tilde{E}(\mathbf{r}) &= \sum_{n=1}^{N_{\text{BS}}} \left(\underbrace{|\mathbf{e}_{\text{ref}}[n]|^2 \bar{\mathbf{e}}_{\text{obj}}[n] g^* \left(\mathbf{r}_{\text{BS}}^{(n)}, \mathbf{r} \right)}_{\text{desired}} + \underbrace{(\mathbf{e}_{\text{ref}}[n])^2 \bar{\mathbf{e}}_{\text{obj}}^*[n] g^* \left(\mathbf{r}_{\text{BS}}^{(n)}, \mathbf{r} \right)}_{\text{interference}} \right) \\ &= A^2 \sum_{\ell=0}^L \bar{\alpha}_{\ell} \left(\tilde{E}_{\ell}^{\text{d}}(\mathbf{r}) + \tilde{E}_{\ell}^{\text{i}}(\mathbf{r}) \right) + \tilde{E}^{\text{n}}(\mathbf{r}),\end{aligned}$$

namely, the **desired**, the **interference**, and the noise-related terms.

Analysis

Proposition

As the wavenumber $\kappa \rightarrow \infty$ and the number of antennas at BS side $N_{\text{BS}} \rightarrow \infty$,

$$\lim_{\substack{\kappa \rightarrow \infty \\ N_{\text{BS}} \rightarrow \infty}} |\tilde{E}_{\ell}^{\text{d}}(\mathbf{r})| = \begin{cases} \sum_{n=1}^{N_{\text{BS}}} \frac{1}{d^{(\ell,n)}} & \text{if } \mathbf{r} = \mathbf{r}_{\text{S}}^{(\ell)}, \\ 0 & \text{otherwise,} \end{cases}$$

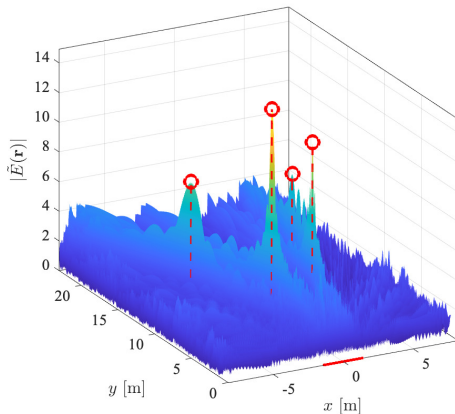
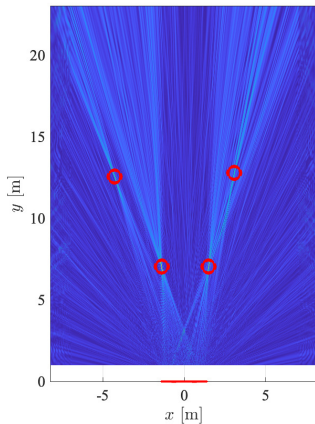
$$\lim_{\substack{\kappa \rightarrow \infty \\ N_{\text{BS}} \rightarrow \infty}} |\tilde{E}_{\ell}^{\text{i}}(\mathbf{r})| = 0,$$

$$\lim_{N_{\text{BS}} \rightarrow \infty} |\tilde{E}^{\text{n}}(\mathbf{r})| = 0.$$

- $\tilde{E}(\mathbf{r})$ exhibits peaks at locations of UE and scatterers while diminishing to 0 everywhere else

Reconstruction Demo on Meshgrid

- Reconstruction example for one UE and three scatterers.



Accelerate Reconstruction via FFT

- Enumerating $\tilde{E}(\mathbf{r}^{(i,j)})$ at all possible locations can be computationally heavy
- Reconstruction formula at the (i, j) grid

$$\tilde{E}(\mathbf{r}^{(i,j)}) = \sum_{n=1}^{N_{\text{BS}}} \mathbf{\bar{h}}[n] \mathbf{e}_{\text{ref}}[n] e^{j\kappa \sqrt{(x_{\text{BS}}^{(n)} - x_i)^2 + y_j^2}}. \quad (1)$$

- Let

$$\bar{\mathbf{h}} = \mathbf{\bar{h}} \odot \mathbf{e}_{\text{ref}}$$

$$\bar{\mathbf{g}}_j = [e^{j\kappa \sqrt{x_1^2 + y_j^2}}, \dots, e^{j\kappa \sqrt{x_{G_x}^2 + y_j^2}}]^T,$$

(1) can be formulated as a **convolution** and implemented by **FFT**

$$\tilde{E}(\mathbf{r}^{(:,j)}) = \left| \mathcal{F}_{G'_x}^{-1} \left[\mathcal{F}_{G'_x} [\bar{\mathbf{h}}] \odot \mathcal{F}_{G'_x} [\bar{\mathbf{g}}_j] \right]_{N_{\text{BS}}:G'_x - N_{\text{BS}} - 1} \right|.$$

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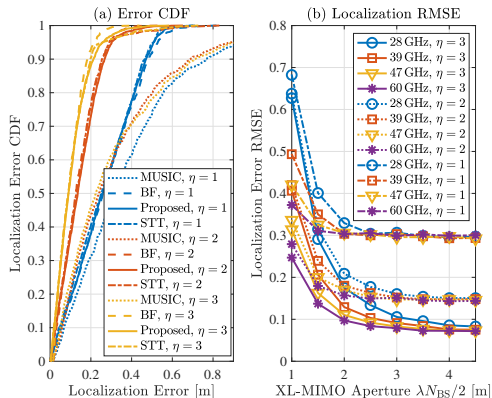
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Numerical Results: Localization



- Comparable CDFs with benchmarks
- No need for baseband sampling via ADCs
- Tens of orders of magnitude reduction in complexity

Figure 6: (a) The CDF of localization error; (b) RMSE of the localization algorithm with varying carrier frequencies and XL-MIMO aperture.

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Channel Sparse Representation

■ Compressive sensing

$$\min_{\tilde{\mathbf{h}}} \|\tilde{\mathbf{h}}\|_0, \quad \text{s.t. } \|\Phi\Psi\tilde{\mathbf{h}} - \mathbf{y}\|_2 \leq \varepsilon,$$

- ▶ $\mathbf{y}$: Received signal
- ▶ Φ : Measurement matrix
- ▶ $\tilde{\mathbf{h}}$: Sparse support vector to be estimated
- ▶ Ψ : Dictionary

■ Challenges in NF channel estimation

- ▶ Two DoFs require more codewords in $\Psi \Rightarrow$ Bulky dictionary
- ▶ Higher rank NF channel $\Rightarrow$ Excessive pilot length τ

Sensing-Enhanced Channel Estimation

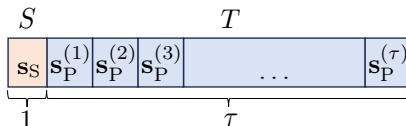


Figure 7: Proposed sensing-enhanced uplink channel estimation protocol.

- One additional slot for localization
- Localization results are utilized in channel estimation during transmission stage
- Only adding one sensing slot will significantly reduce pilot length τ and size of dictionary Ψ

Dictionary Design

- Channel matrix $\mathbf{H}$ can be properly sparsified via its SVD $\mathbf{H} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^H$
 $\Rightarrow \mathbf{\Psi} = \mathbf{V}^* \otimes \mathbf{U}$

- Consider the EVD of auto-correlation $\mathbf{R}_{\text{BS}} = \mathbb{E} [\mathbf{H}\mathbf{H}^H]$
- Introducing paraxial approximation [2]

$$\mathbf{R}_{\text{BS}}[n', n] \simeq \gamma_n \mathbb{1}\{n = n'\} + \frac{1}{r_0^2} \sum_{m=1}^{N_{\text{UE}}} e^{-j\kappa \frac{(x_{\text{BS}}^{(n)} - x_{\text{UE}}^{(m)})^2 - (x_{\text{BS}}^{(n')} - x_{\text{UE}}^{(m)})^2}{2\hat{y}^{(0)}}}$$

► $\hat{y}^{(0)}$: Estimate of the UE location

$$\gamma_n = \frac{1}{L} \sum_{\ell=1}^L \sum_m^{N_{\text{UE}}} \frac{1}{\|\mathbf{r}_{\text{UE}}^{(m)} - \hat{\mathbf{r}}_{\text{S}}^{(\ell)}\|^2 \|\mathbf{r}_{\text{BS}}^{(n)} - \hat{\mathbf{r}}_{\text{S}}^{(\ell)}\|^2}$$

[2] D. A. B. Miller, "Communicating with waves between volumes: Evaluating orthogonal spatial channels and limits on coupling strengths," *Appl. Opt.*, vol. 39, no. 11, pp. 1681–1699, Apr. 2000.

Dictionary Design

- Rewrite the auto-correlation as

$$\mathbf{R}_{\text{BS}}[n', n] \simeq \gamma_n \mathbb{1}\{n = n'\} + e^{j\kappa \frac{(x_{\text{BS}}^{(n')})^2 - (x_{\text{BS}}^{(n)})^2}{2\hat{y}^{(0)}}} \bar{\mathbf{R}}_{\text{BS}}[n', n]$$

- The structure of auto-correlation suggests that the following EVD holds

$$\mathbf{R}_{\text{BS}} \mathbf{u}_n = \mathbf{D}_{\text{BS}}^{-1} (\mathbf{\Gamma} + \bar{\mathbf{R}}_{\text{BS}}) \mathbf{D}_{\text{BS}} \mathbf{u}_n = \lambda_n \mathbf{u}_n.$$

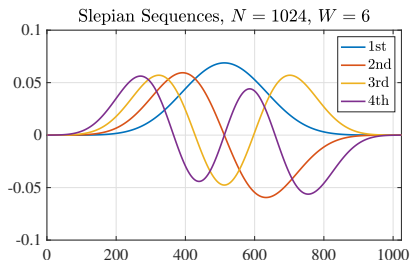
- The matrix $\bar{\mathbf{R}}_{\text{BS}}[n', n]$ is a **Toeplitz Sinc** matrix

$$\bar{\mathbf{R}}_{\text{BS}}[n', n] = \frac{1}{r_0^2} \sum_{m=1}^{N_{\text{UE}}} e^{j\kappa \frac{x_{\text{UE}}^{(m)} (x_{\text{BS}}^{(n)} - x_{\text{BS}}^{(n')})}{\hat{y}^{(0)}}} \propto \frac{\sin \left[2\pi W (x_{\text{BS}}^{(n)} - x_{\text{BS}}^{(n')}) \right]}{(x_{\text{BS}}^{(n)} - x_{\text{BS}}^{(n')})},$$

where $W = \kappa L_{\text{R}} / (4\pi \hat{y}^{(0)})$.

Dictionary Design

- The eigenvectors of $\{\mathbf{u}_n\}_{n=1}^{N_{BS}}$ of auto-correlation matrix $\overline{\mathbf{R}}_{BS}[n', n]$ are known as *discrete prolate spheroidal sequence* (DPSS) or *Slepian sequence* [3] within frequency W

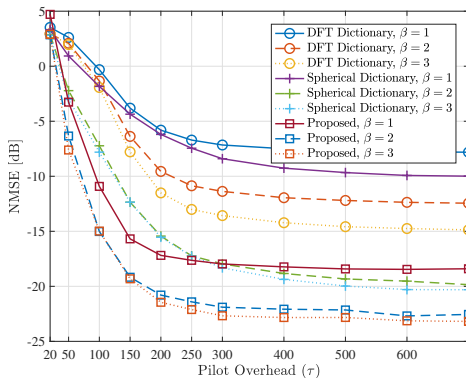


- Estimation of the auto-correlation and its EVD requires numerous samples. The **closed-form** solution here make it efficient to generate the dictionary.

[3] D. Slepian, "Estimation of signal parameters in the presence of noise," *IRE Trans. Inf. Theory*, vol. 3, no. 3, pp. 68–89, 1954.

Numerical Results: Pilot Overhead

■ Near-field CE error with $I = 30$ OMP iterations



■ To achieve a CE NMSE of -10 dB, the proposed method saves up to 85.7% of the pilot overhead when compared to the spherical dictionary [4]

Figure 8: Performance comparison of near-field channel estimation error versus pilot length.

[4] M. Cui and L. Dai, "Channel estimation for extremely large-scale MIMO: Far-field or near-field?" *IEEE Trans. Commun.*, vol. 70, no. 4, pp. 2663–2677, 2022

Numerical Results: Dictionary Size

■ Minimum required dictionary size for target NMSE

Dictionaries	Baseband Samples			Dictionary Size		
	Target NMSE					
	-15 dB	-20 dB	-25 dB	-15 dB	-20 dB	-25 dB
DFT	256	358	410	2,304	4,096	4,096
Spherical [4]	205	358	N/A	1,620	4,096	N/A
Proposed	154	174	205	$1,024+L$	$1,024+L$	$1,024+L$

- A drastic reduction in baseband samples and dictionary size by up to 67% and 66%, respectively

[4] M. Cui and L. Dai, "Channel estimation for extremely large-scale MIMO: Far-field or near-field?" *IEEE Trans. Commun.*, vol. 70, no. 4, pp. 2663–2677, 2022.

Summary

- **Power measurement** works under near-field XL-MIMO
- **Sensing** results help reduce the pilot overhead and ensued baseband samples
- **Eigen-dictionary** saves storage and promote convergence

Paper Info

[J1] S. Liu, X. Yu, Z. Gao, J. Xu, D. W. K. Ng, and S. Cui, “Sensing enhanced channel estimation for near-field XL-MIMO systems,” *IEEE J. Sel. Areas Commun.*, vol. 43, no. 3, pp. 628-643, Mar. 2025.

Latest update: <https://arxiv.org/pdf/2403.11809>

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Position Reconfigurable Antenna Arrays

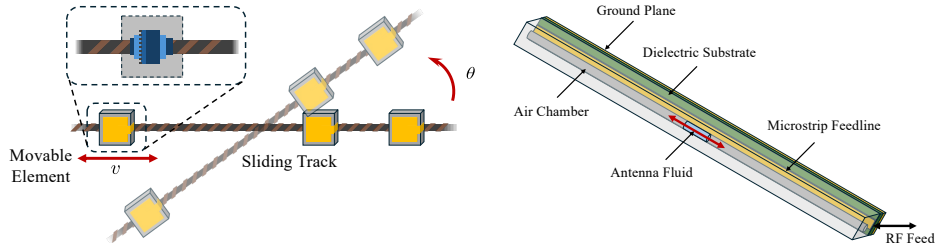


Figure 9: Implementations of position reconfigurable arrays (PRAs): Movable antennas (Left) and fluid antennas (Right).

- Antenna positions offer new design DoFs for wireless systems [5]

[5] L. Zhu, W. Ma, and R. Zhang, "Movable antennas for wireless communication: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 62, no. 6, pp. 114–120, 2024.

Motivations

Limitations of current research works

- ▶ High **computational complexity**, lack of **scalability** with **massive** antennas
- ▶ Lack of system-level design **insights**
- ▶ Neglect of **near-field** effects

What we provide:

- ▶ Acceptable complexity, scalable for **massive/XL-MIMO**
- ▶ Provide **closed-form solutions** with physical insights
- ▶ Suitable for **near-field** scenarios

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System Model

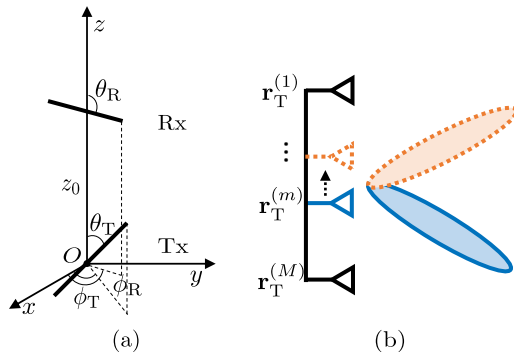


Figure 10: Near-field scenario and movable antennas.

- Downlink point-to-point with dominant LoS channel
- M movable antennas at BS (Tx), N fixed antennas at UE (Rx)

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Antenna Position Function

- Antennas move freely on a linear array with coordinate

$$\begin{cases} x_T^{(m)} &= \frac{A_T}{2} f(m) \sin \theta_T \cos \phi_T \\ y_T^{(m)} &= \frac{A_T}{2} f(m) \sin \theta_T \sin \phi_T, \quad \forall m \in \mathcal{M}, \\ z_T^{(m)} &= \frac{A_T}{2} f(m) \cos \theta_T \end{cases}$$

where

- ▶ $\mathcal{M} = \{m \in \mathbb{Z} \mid 1 \leq m \leq M\}$
- ▶ $A_T = (M - 1)d$, aperture.
- $p = f(m) \in [-1, 1]$ is the continuous **antenna position function** (APF).
- For ULA case, APF is given by

$$f^{\text{uni}}(m) = \frac{2}{M - 1} \left(m - \frac{M + 1}{2} \right).$$

Antenna Density Function

- The number of antenna elements within unit length

$$w(p) = \lim_{\Delta p \rightarrow 0} \frac{f^{-1}(p + \Delta p) - f^{-1}(p)}{\Delta p} = \frac{d}{dp} f^{-1}(p),$$

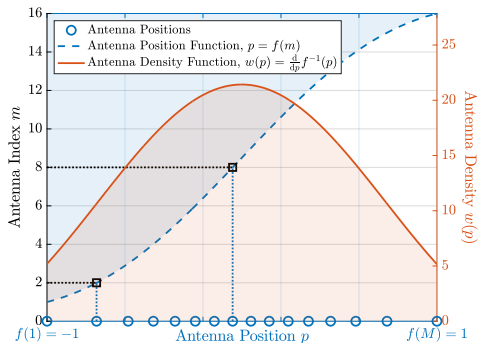


Figure 11: APF $p = f(m)$ (in blue) and ADF $w(p)$ (in orange).

Problem Formulation

- Find optimal $w(p)$ to maximize the achievable rate *functional*

$$C_w = \log_2 \det \left(\mathbf{I} + \frac{P_T}{M\sigma_n^2} \mathbf{H}_w \mathbf{H}_w^H \right)$$

- We shall study the property of Toeplitz matrix

$$\mathbf{T}_N = \mathbf{I} + \frac{\rho}{M} \mathbf{H}_w \mathbf{H}_w^H \triangleq \mathbf{I} + \rho \bar{\mathbf{K}}_w$$

- Goal:** To optimize ADF $w(p)$ that maximizes $\log \det_2(\mathbf{T}_N)$

Useful Preliminaries

Definition 1: Generating Function of Toeplitz Matrix

Let $s(\theta)$ be a real smooth and non-vanishing function defined on unit circle with Fourier coefficients

$$c_k = \frac{1}{2\pi} \int_0^{2\pi} s(\theta) e^{-jk\theta} d\theta, \quad k \in \mathbb{Z}.$$

If a Toeplitz matrix $\mathbf{T}_N$ admits the form as

$$\mathbf{T}_N = \begin{bmatrix} c_0 & c_{-1} & c_{-2} & \cdots & c_{1-N} \\ c_1 & c_0 & c_{-1} & \cdots & c_{2-N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ c_{N-1} & c_{N-2} & c_{N-3} & \cdots & c_0 \end{bmatrix},$$

then $s(\theta)$ is called the **generating function** of $\mathbf{T}_N$.

ADF and Generating function

- A Toeplitz matrix $\mathbf{T}_N$ is associated with its generating function $s(\theta)$
- We proved that the generating function of $\mathbf{T}_N = \mathbf{I} + \rho \overline{\mathbf{K}}_w$ is closely related to the ADF $w(p)$, given by

$$s(\theta) = 1 + \frac{2\pi\rho}{\beta z_0^2 \left(1 + \tau \left(\frac{\theta}{\beta}\right)\right)^2} w\left(\frac{\theta}{\beta}\right),$$

where $\beta = \frac{\kappa A_T A_R \sin \theta_T \sin \theta_R \cos(\phi_T - \phi_R)}{z_0(N-1)}$ and $\tau = \frac{A_T}{2z_0} \cos \theta_T$ are two antenna geometry-related parameters.

- **Goal transfer:** Optimize $s(\theta)$ to maximize $\log \det_2(\mathbf{T}_N)$

Optimal ADF

Fisher-Hartwig Theorem [6], [7]

The optimal generating function

$$s^*(\theta) \propto |1 - \cos(\theta - \beta)|^\alpha |1 - \cos(\theta + \beta)|^\alpha, \quad -\frac{1}{2} < \alpha < 0$$

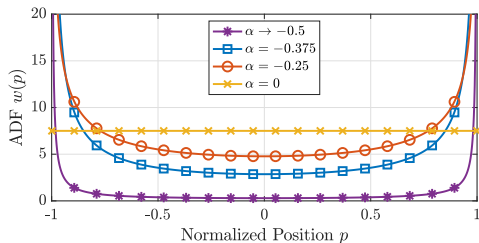
■ Substituting Maclaurin series $1 - \cos \theta = \theta^2/2 + \mathcal{O}(\theta^2)$

$$s^*(\theta) \propto \frac{1}{(\beta^2 - \theta^2)^{-2\alpha}} \Rightarrow w^*(p) = \left(\frac{\gamma_\alpha}{(1 - p^2)^{-2\alpha}} - \frac{\beta z_0^2}{2\pi\rho} \right) (1 + \tau p)^2$$

[6] M. E. Fisher and R. E. Hartwig, “Toeplitz determinants: Some applications, theorems, and conjectures,” in *Advances in Chemical Physics*. John Wiley & Sons, Ltd, 1969, pp. 333–353.

[7] A. Lenard, “Some remarks on large Toeplitz determinants,” *Pacific Journal of Mathematics*, vol. 42, no. 1, pp. 137–145, 1972.

A Glimpse of ADF



- $\alpha = 0 \Leftrightarrow$ ULA
- “U”-shape: a denser deployment of antenna elements at the edges of the array efficiently captures the higher spatial frequency of spherical waves at the array periphery

Log-Det in the Rate Functional

Fisher-Hartwig Theorem [6], [7]

$$\begin{aligned}
 C_w &= \log \det (\mathbf{I} + \rho \bar{\mathbf{K}}_w) \\
 &= \log N \sum_{r=1}^2 \alpha_r^2 + \sum_{r=1}^2 \frac{BG^2(1 + \alpha_r)}{BG(1 + 2\alpha_r)} + (2 - 2 \cos 2\beta)^{-\alpha_1 \alpha_2} + \mathbf{const},
 \end{aligned}$$

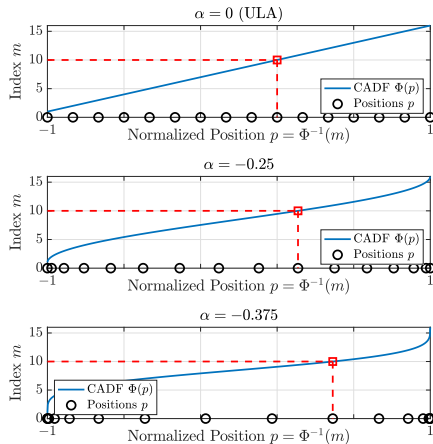
where $BG(\cdot)$ denotes the Barnes G-function.

- When $N \rightarrow \infty$, $\frac{dC_w}{d\alpha_i} < 0$
- The smaller the α is, the denser antenna deployment at two edges, and the higher spectral efficiency achieved

-
- [6] M. E. Fisher and R. E. Hartwig, “Toeplitz determinants: Some applications, theorems, and conjectures,” in *Advances in Chemical Physics*. John Wiley & Sons, Ltd, 1969, pp. 333–353.
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Discretization

■ $M = 16$ Antenna positions on a normalized linear array

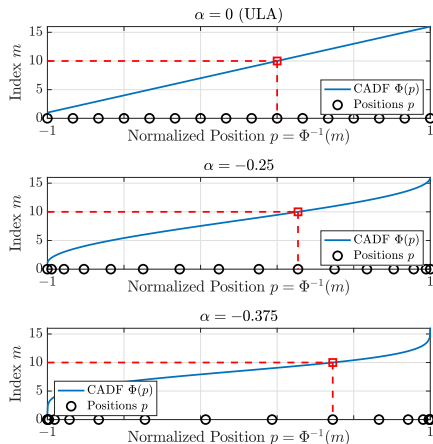


■ $\alpha \uparrow \Rightarrow$ 1) $C_w \uparrow$ 👍
2) Antenna spacing $\downarrow$ 🚫

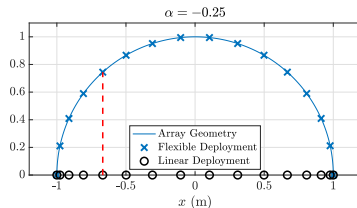
[8] S. Liu and X. Yu, "Low-complexity near-field localization with XL-MIMO sectored uniform circular arrays," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, 2024, pp. 4756–4761

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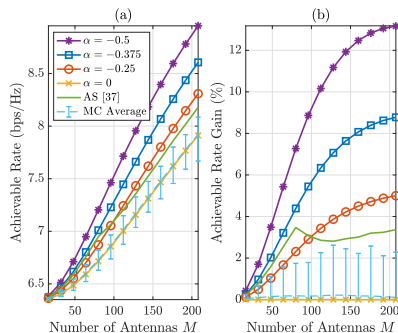
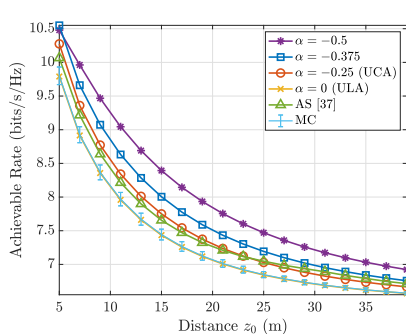
- $\alpha \uparrow \Rightarrow 1) C_w \uparrow$
- 2) Antenna spacing $\downarrow$
- $\alpha = -0.25 \leftrightarrow$ uniform circular array (UCA) [8]



[8] S. Liu and X. Yu, "Low-complexity near-field localization with XL-MIMO sectored uniform circular arrays," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, 2024, pp. 4756–4761

Numerical Results

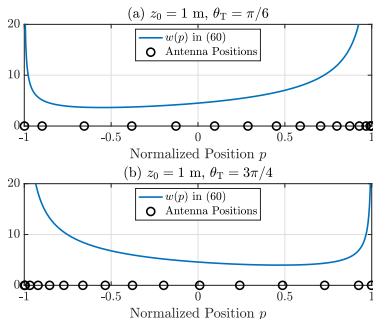
- Antenna positions have significant effect on achievable rate
- By simply adopting UCA, achievable rate can be improved



- Up to 13% performance gain by closed-form solution

Numerical Results

Optimal ADF for different incident directions [▶ Link](#)



- Antennas tend to cluster towards the incident direction
- Higher wavefront curvature of the EM wave at the near end of the array
- Higher sampling rate at the near end in the near-field region

Summary

- Antenna positions can affect the intrinsic structure of channel matrix
- **Closed-form** ADF can be obtained to maximize the achievable rate
- **Edge antenna density** has a significant effect on capacity (up to 13%)

Paper Info

[J2] S. Liu, X. Yu, J. Xu, and R. Zhang, “Near-field communication with massive movable antennas: A functional perspective,” *under major revision*.

- However, the discretization process may result in some performance loss

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Outline

- 1 Introduction
- 2 Near-Field S&C with Power Sensors at Antennas
 - Power Sensor-Enabled Localization
 - Power Sensor-Enhanced Channel Estimation
- 3 **Near-Field Communications with Movable Antennas**
 - A Functional Perspective
 - **A Discrete Approach**
- 4 Conclusion

Analysis of Spectral Efficiency

- Under a typical near-field communication setting

$$R_{\mathbf{x}} = \log_2 \det \left(\mathbf{I}_N + \frac{\rho}{M} \mathbf{H}_{\mathbf{x}} \mathbf{H}_{\mathbf{x}}^H \right) \\ \simeq \log_2 \det (\mathbf{D}_{\mathbf{T}} \mathbf{D}_{\mathbf{T}}^H) + \log_2 \det \left((\mathbf{V}_{\mathbf{T}})^H \mathbf{V}_{\mathbf{T}} \right) + \text{const},$$

where $\mathbf{x} = [x_{\text{BS}}^{(1)}, x_{\text{BS}}^{(2)}, \dots, x_{\text{BS}}^{(M)}]$ are antenna positions,

$$\mathbf{D}_{\mathbf{T}} = \text{diag} \left(\left[\frac{e^{j\kappa r_1}}{r_1}, \frac{e^{j\kappa r_2}}{r_2}, \dots, \frac{e^{j\kappa r_M}}{r_M} \right] \right) \quad \Leftarrow \text{Diagonal}$$

$$\mathbf{V}_{\mathbf{T}} = \begin{bmatrix} 1 & \sin(\varphi_1 - \theta_{\text{UE}}) & \sin^2(\varphi_1 - \theta_{\text{UE}}) & \cdots \\ 1 & \sin(\varphi_2 - \theta_{\text{UE}}) & \sin^2(\varphi_2 - \theta_{\text{UE}}) & \cdots \\ \vdots & \vdots & \vdots & \cdots \\ 1 & \sin(\varphi_M - \theta_{\text{UE}}) & \sin^2(\varphi_M - \theta_{\text{UE}}) & \cdots \end{bmatrix} \quad \Leftarrow \text{Vandermonde}$$

Problem Formulation

■ *Weighted Fekete problem* [9]

$$\begin{aligned} \max_{\mathbf{s}} \quad & 2 \sum_{1 \leq i < j \leq M} \log_2(s_j - s_i) + \sum_{m=1}^M \log_2(1 - \tilde{s}_m^2) \\ \text{s.t.} \quad & s_{\min} = s_1 < s_2 < \cdots < s_M = s_{\max}, \end{aligned}$$

where $s_m = \sin(\varphi_m - \theta_{\text{UE}})$ and $\tilde{s}_m = \sin \varphi_m = \sin(\arcsin s_m + \theta_{\text{UE}})$

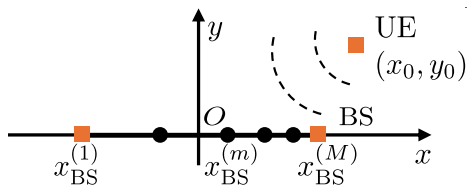
■ Proved to be *convex*

■ Physical insights

[9] E. B. Saff and V. Totik, *Logarithmic Potentials with External Fields* (Grundlehren der mathematischen Wissenschaften), Second. Cham, Switzerland: Springer, 1997, vol. 316, ISBN: 978-3-031-65133-5.

Weighted Fekete Problem

- Weighted Fekete problem seeks the optimal distribution of M charges achieves a balance between **internal** interaction mutual repulsion and **external** influence



- Mutual coupling among antennas corresponds to the **internal** interaction
- The field induced by the UE serves as the **external** field
- Positions of $M - 2$ movable antennas have to be delicately optimized to obtain a state of equilibrium between these two forces

Greedy Position Selection

- To relax the computational complexity of convex optimization algorithms ($\sim \mathcal{O}(M^3)$), we introduce greedy antenna selection
- Select the **next** antenna position that maximize the **local optimal** rate
- For the m -th antenna, define the **local objective** (c.f. Page 48)

$$J(s) = 2 \sum_{i=1}^{m-1} \log_2 |s_i^* - s| + \log_2 (1 - \sin^2 (\arcsin s + \theta_{\text{UE}}))$$

- Do

Update Feasible Region $\mathcal{S} \quad \Leftrightarrow \quad \text{Find } s_m^* = \arg \max_{s \in \mathcal{S}} (J(s))$

Until all $M - 2$ antenna elements are assigned

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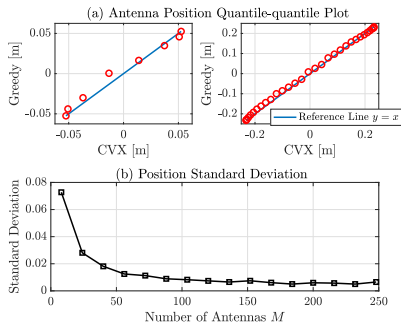
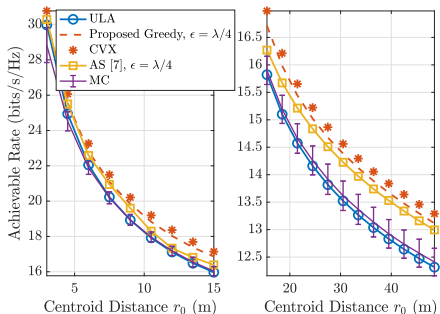
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Greedy Position Selection

- (Left) Achieve higher rates with limited performance degradation compared to CVX.
- (Right) Greedy positions show distributional conformity with CVX results.



Summary

- The movable antenna placement problem in the near field is closely related to the classic potential energy equilibrium theory
- Efficient greedy algorithm can be applied to antenna positioning to maximize the achievable rate

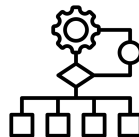
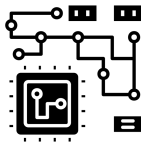
Paper Info

- [C1] S. Liu and X. Yu, “Near-field line-of-sight communication with massive movable antennas,” submitted to *IEEE Int. Conf. Commun. (ICC)*, Glasgow, Scotland, UK, May 2026.

Outline

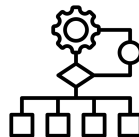
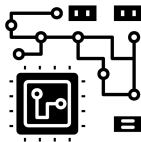
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- ④ **Conclusion**

Conclusion



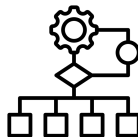
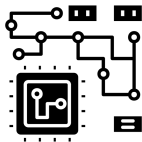
	Hardware	Algorithm

Conclusion



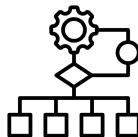
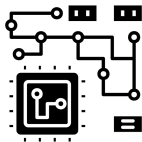
	Hardware	Algorithm
Localization	Power sensors	Back projection
Channel estimation		DPSS dictionary

Conclusion



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Conclusion



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- Tailored hardware and low-complexity algorithms for near-field S&C

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Thanks for your attention!

Q & A

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sc.liu@my.cityu.edu.hk

Slides & Codes: <https://github.com/scliubit/sensing-ce-xlmimo>