



# **Movable Antennas for Wireless Communication and Sensing: Fundamental Gain and Practical Design**

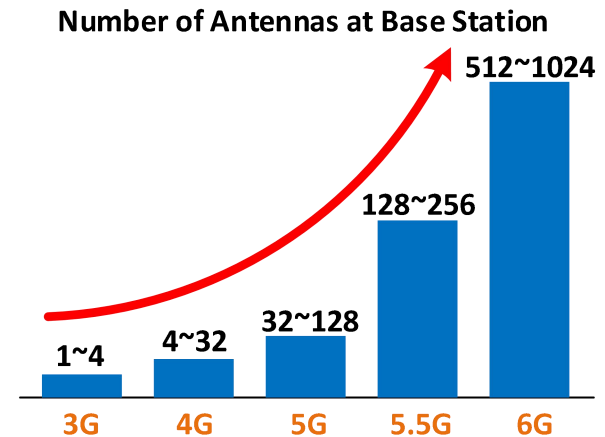
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**Beijing Institute of Technology**  
**24 October 2026**

# Outline

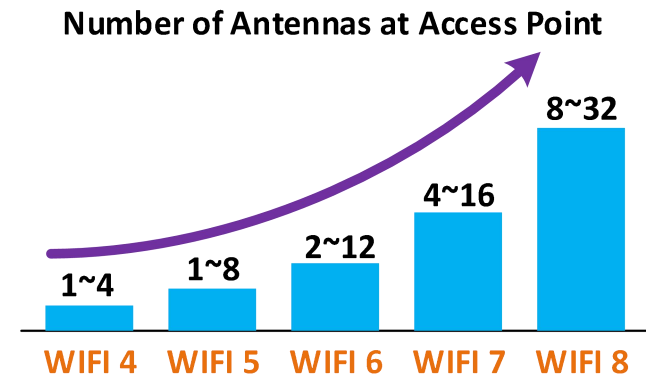
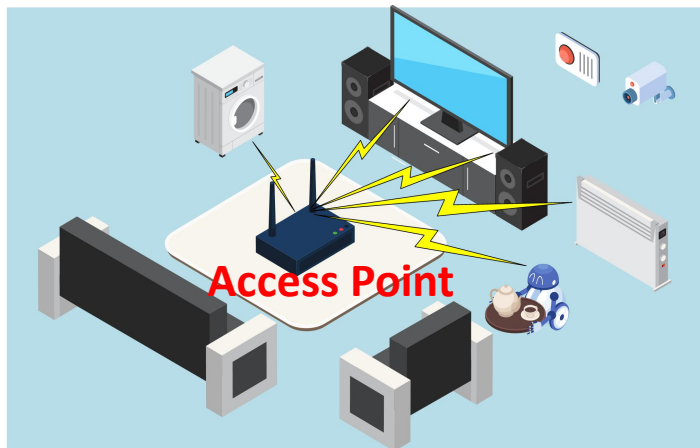
- ❑ Introduction of Movable Antenna
- ❑ MA System Design Based on Channel Statistics
- ❑ Efficient MA Architectures
- ❑ MA for Wireless Sensing
- ❑ Conclusions and Future Directions

# MIMO Evolution

Cellular  
Networks

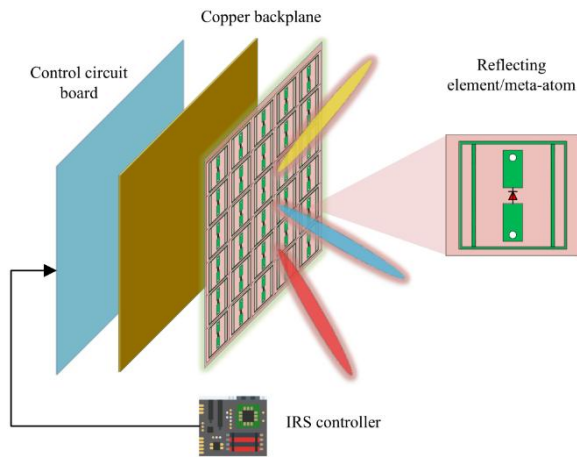


WiFi  
Networks

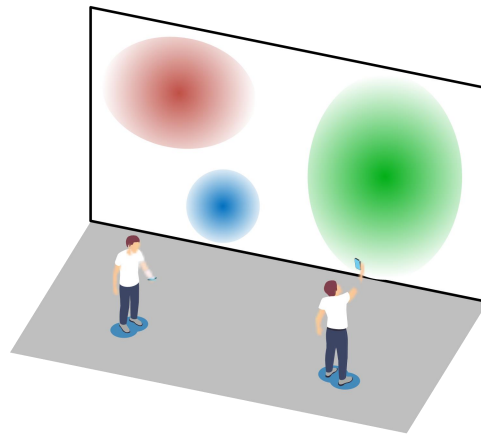


- ❑ Increasingly **more antennas** to achieve higher data rate
- ❑ How to achieve **cost-effective** MIMO for future wireless networks?

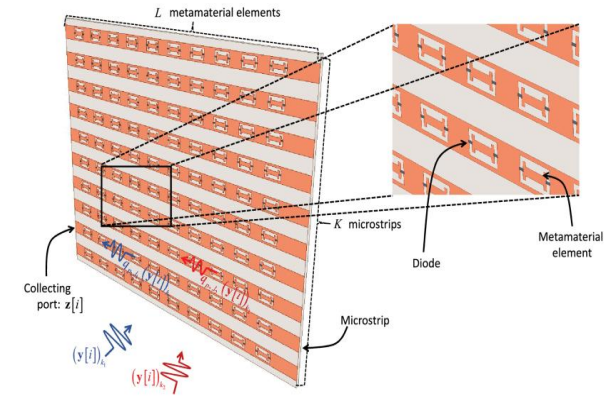
# Recent Development: “MetaMIMO”



Intelligent surfaces (IRS/RIS)<sup>[1]</sup>



Holographic MIMO<sup>[2]</sup>

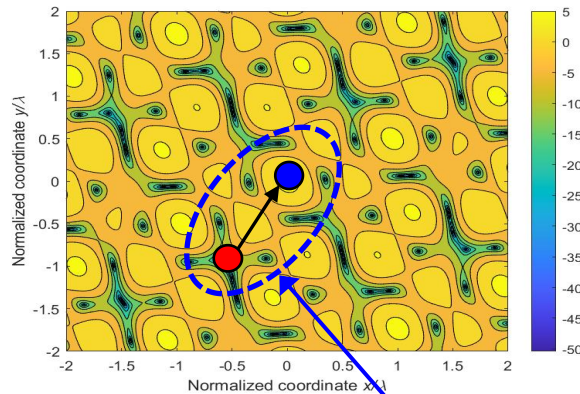


Dynamic metasurface antennas (DMA)<sup>[3]</sup>

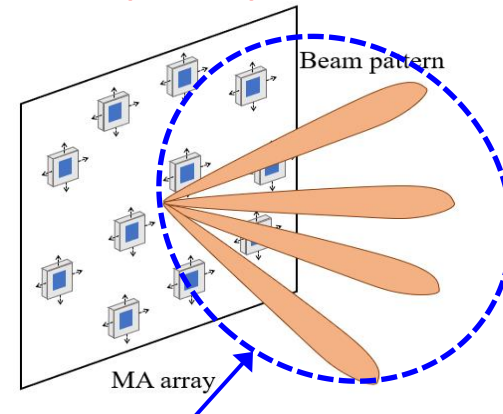
- ❑ MetaMIMO uses reconfigurable, low-cost and energy-efficient **metasurface**
- ❑ Like traditional MIMO, also based on **fixed-position antenna (FPA)**

[1] Q. Wu and R. Zhang, “Towards smart and reconfigurable environment: Intelligent reflecting surface aided wireless network,” IEEE Commun. Mag., vol. 58, no. 1, pp. 106–112, Jan. 2020.  
 [2] A. Pizzo, T. L. Marzetta, and L. Sanguinetti, “Spatially-stationary model for holographic MIMO small-scale fading,” IEEE J. Sel. Areas Commun., vol. 38, no. 9, pp. 1964–1979, Sep. 2020.  
 [3] N. Shlezinger, G. C. Alexandropoulos, M. F. Imani, Y. C. Eldar, and D. R. Smith, “Dynamic metasurface antennas for 6G extreme massive MIMO communications,” IEEE Wireless Commun., vol. 28, no. 2, pp. 106–113, Apr. 2021.

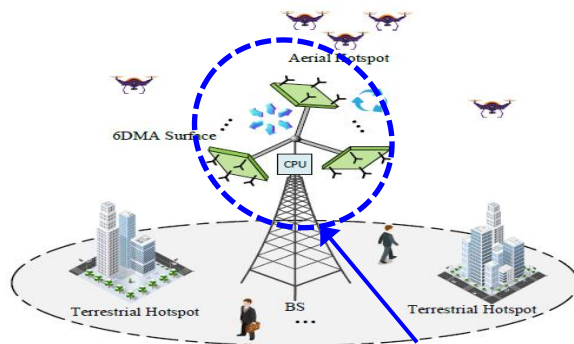
# Why Movable Antenna (MA)?



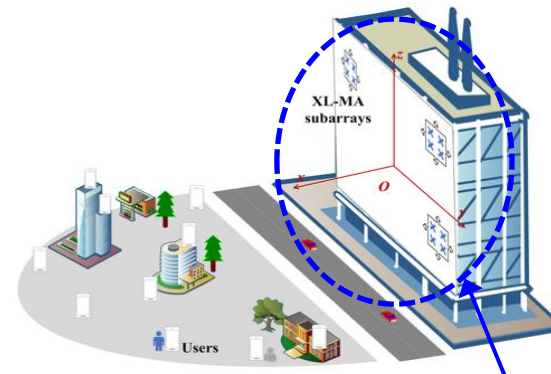
Small-scale 1D/2D/3D antenna movement can improve channel gain by tens of dB



MA array can achieve more flexible beamforming via joint position and weight optimization



6D antenna movement (position and rotation) can improve channel conditions

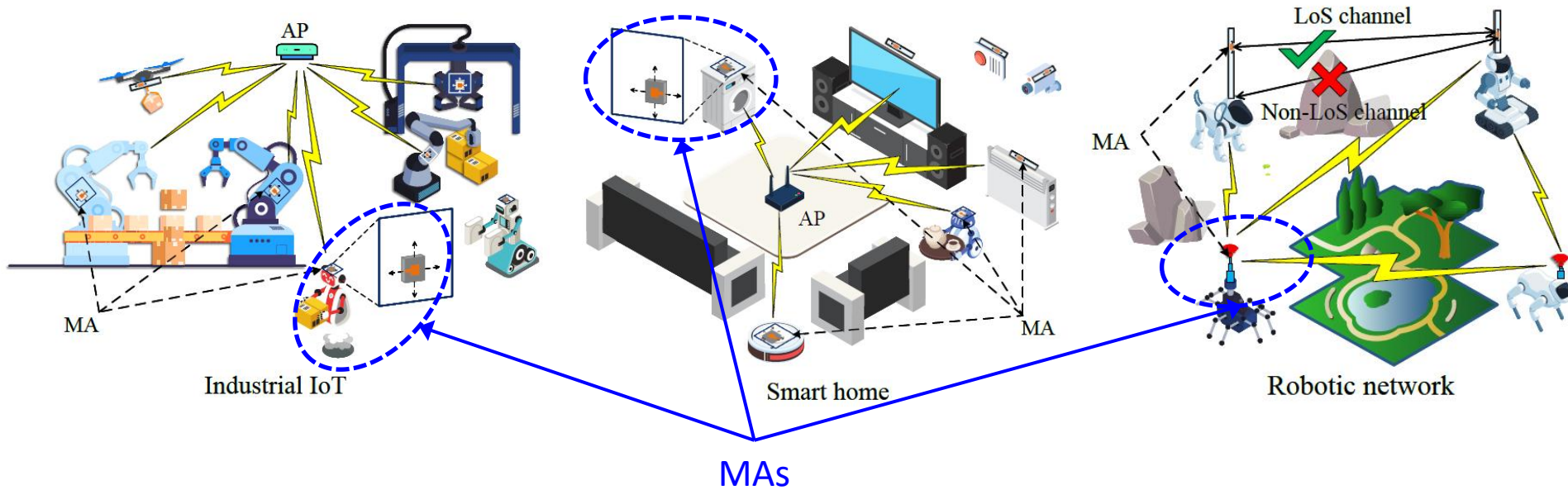


Large-scale antenna movement can improve channel conditions (LoS visibility, large-scale path loss)

## Motivations:

- ❑ Provide new degree of freedom (DoF) to fully exploit channel spatial variation
- ❑ Achieve better performance than traditional FPAs without adding more antennas

# Machine-Type Communications (MTC)



- ❑ MTC devices in confined areas experience **slowly-varying wireless channels**
- ❑ Narrow-band MTC with a small number of antennas usually has **limited time/frequency/spatial diversity**
- ❑ MA can be used to achieve **higher spatial diversity** with even one single MA only

L. Zhu, W. Ma, and R. Zhang, "Movable antennas for wireless communication: Opportunities and challenges," IEEE Communications Magazine, vol. 62, no. 6, pp. 114-120, June 2024.

# Mobile Communications

Adjust the **antenna downtilt** remotely to improve coverage



Huawei: Remote Electrical Tilt (RET) antenna<sup>[1]</sup>

Four **rotatable** antennas to track mobile devices



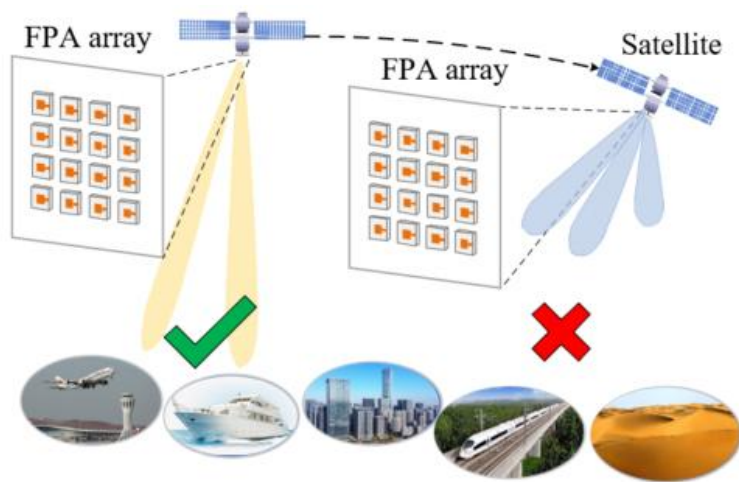
TP-Link: WiFi Router Archer AXE200 Omni<sup>[2]</sup>

- ❑ Partial antenna movement (rotation) at BS/AP can **improve channel conditions**
- ❑ However, **6D movement** of antennas (3D position & 3D rotation) is **not fully explored at BS/AP yet: Motivation for 6D movable antenna (6DMA)**

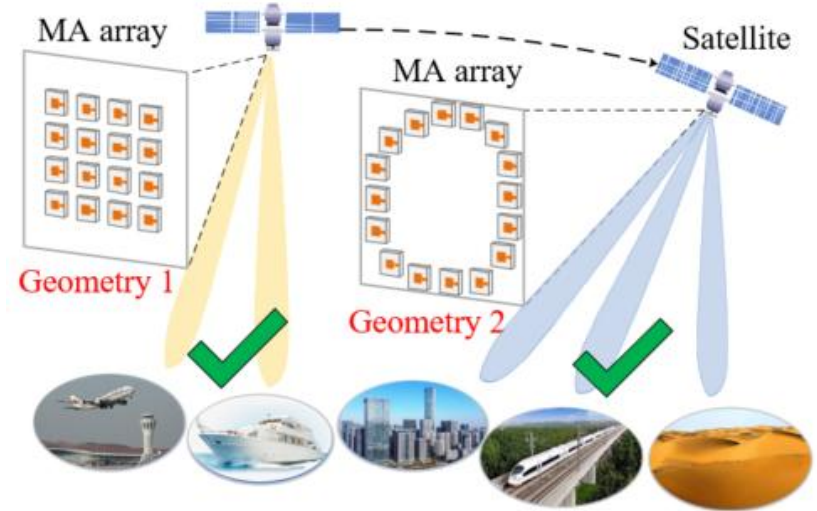
[1] <https://forum.huawei.com/enterprise/en/hcia-lte-%E4%B8%A829-remote-electrical-tilt-introduction/thread/667264004948639744-667213872962088960>

[2] <https://www.tp-link.com/sg/home-networking/wifi-router/archer-axe200-omni/>

# Satellite Communications



FPA array



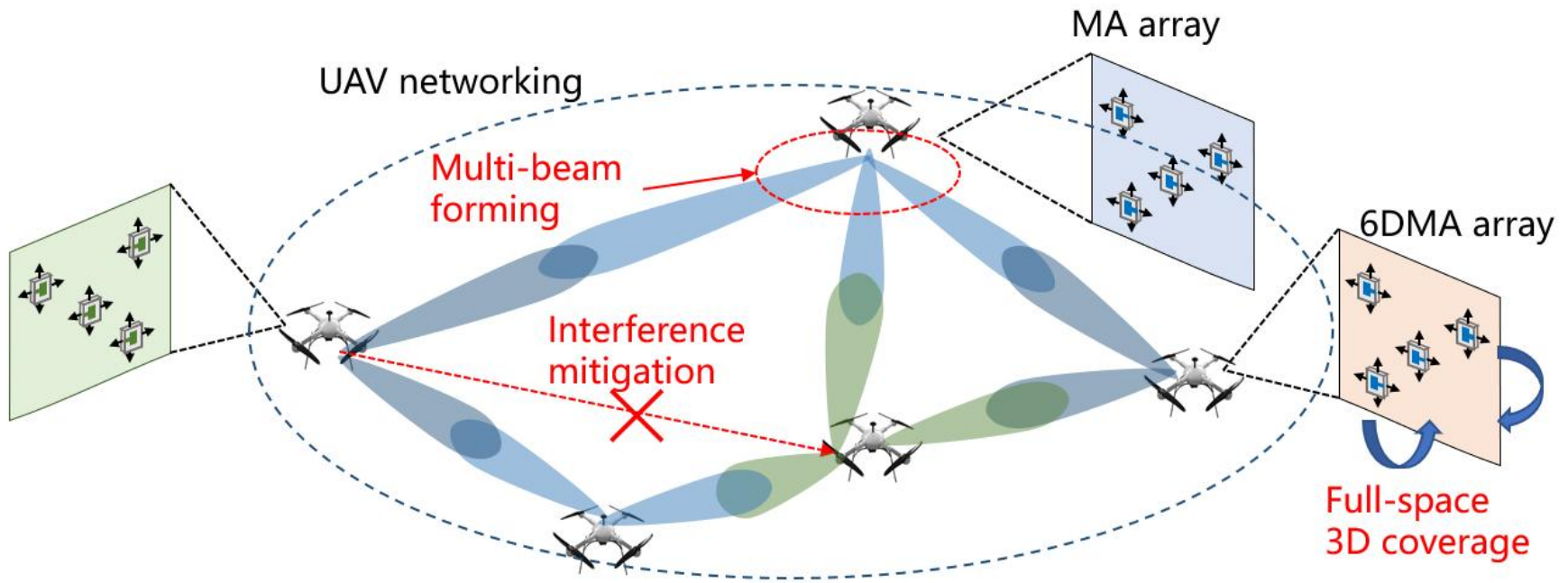
MA array

❑ **Fixed array geometry** can only adapt beam directions via conventional analog/digital beamforming

❑ **Reconfigurable geometry** of MA arrays can enable **more flexible beam** patterns to support ground users with varying coverage requirement

L. Zhu, X. Pi, W. Ma, Z. Xiao, and R. Zhang, "Dynamic beam coverage for satellite communications aided by movable-antenna array," IEEE Transactions on Wireless Communications, 2024.

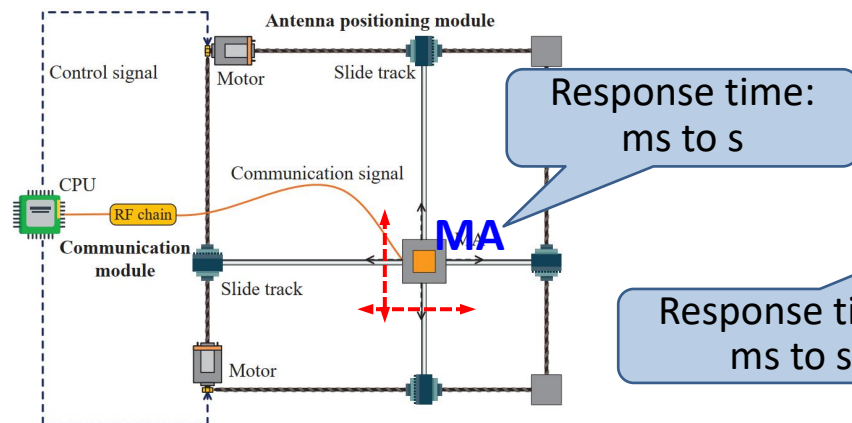
# Airborne Communications



- ❑ FPA arrays has **limited DoFs** in beamforming and coverage
- ❑ MA arrays enable **flexible beamforming** for interference mitigation
- ❑ 6DMA arrays enable **full-space 3D coverage** in dynamic environments

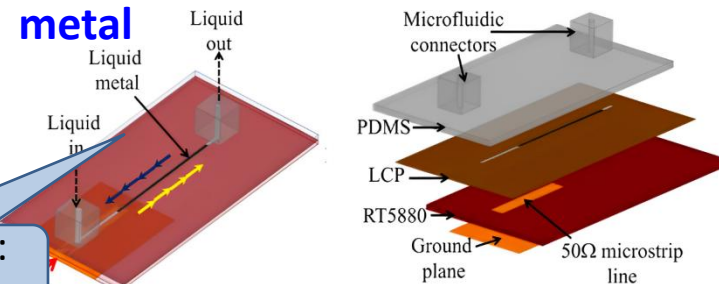
T. Ren, X. Zhang, L. W. Ma, X. Gao, and R. Zhang, "6D Movable Antenna Enhanced Interference Mitigation for Cellular-Connected UAV Communications," IEEE Wireless Communications Letters, 2025.

# Implementations: Movable Element

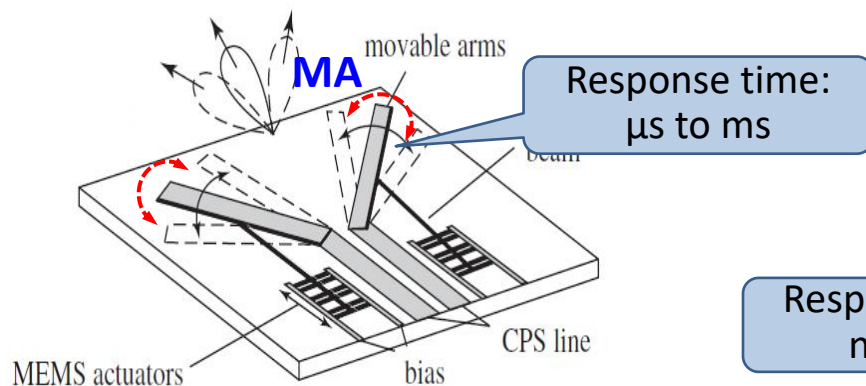


Motor-based Movable Element

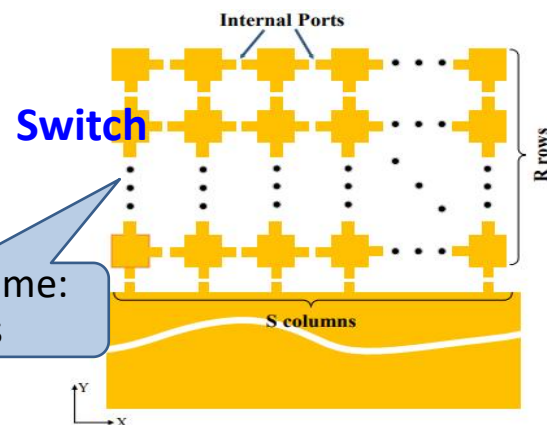
## Liquid metal



Fluid/liquid-based Movable Element

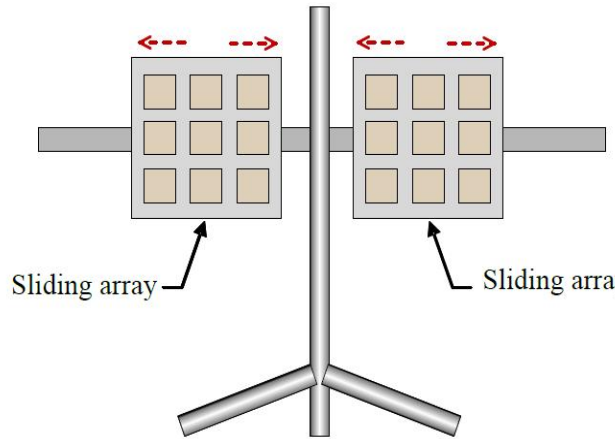


MEMS-based Movable Element

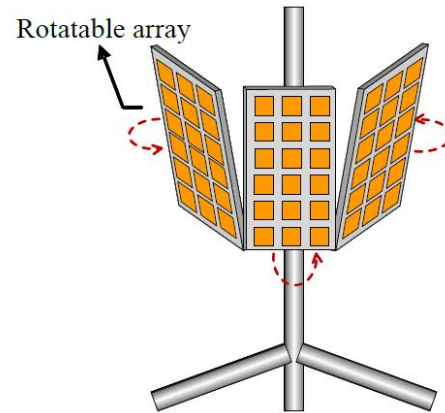


Electronically Reconfigurable Element

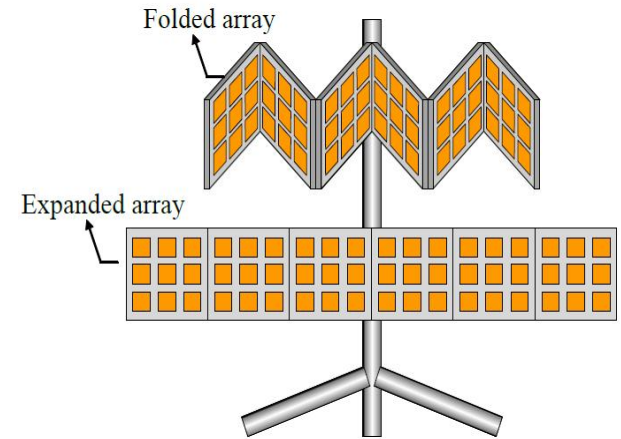
# Implementations: Movable Subarray



Sliding Array



Rotatable Array



Deployable Array

## Limitations:

- ❑ Each movable unit requires an **independent driving component** for position/rotation reconfiguration
- ❑ **Hardware complexity scaling** with the total number of movable elements/subarrays

# Outline

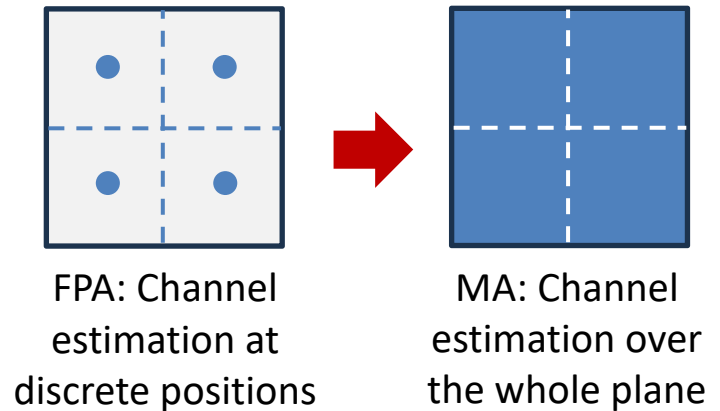
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# Limitations of Instantaneous CSI-Based MA Designs

## ❑ Channel Estimation & Optimization

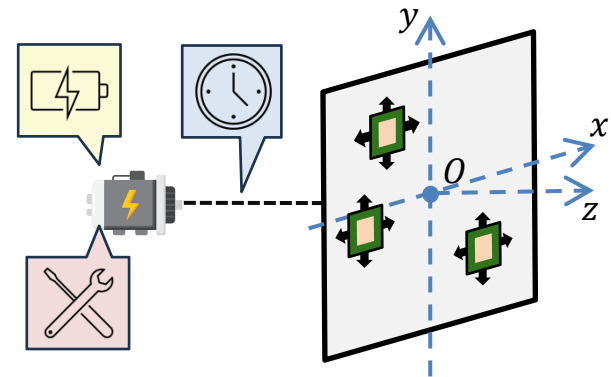
### Challenges

- **Channel estimation overhead**: requires channel knowledge over the MA plane.
- **Optimization overhead**: online antenna position optimization is time-consuming.



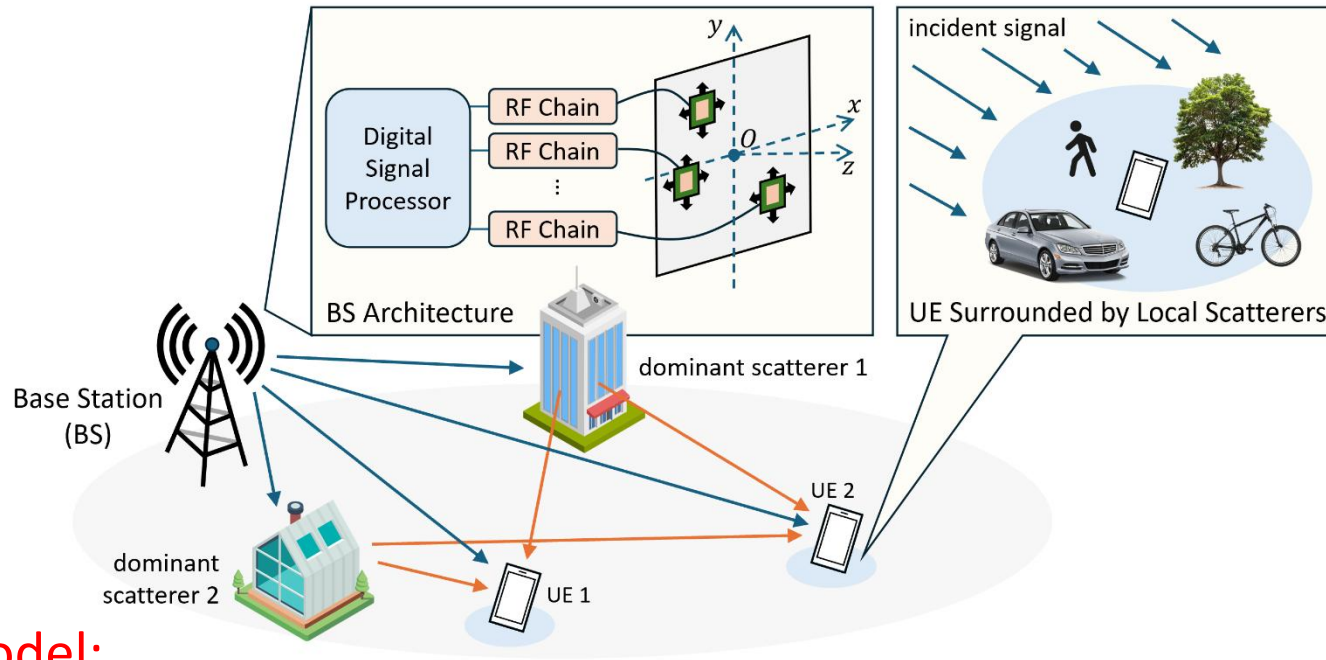
## ❑ High Cost for Frequent Repositioning

- Delays from movement (**may exceed channel coherent time**).
- Power consumption from motors.
- Mechanical wears.



**Solution: design MA positions over a larger timescale to reduce repositioning frequency.**

# MA Optimization Based on Statistical CSI

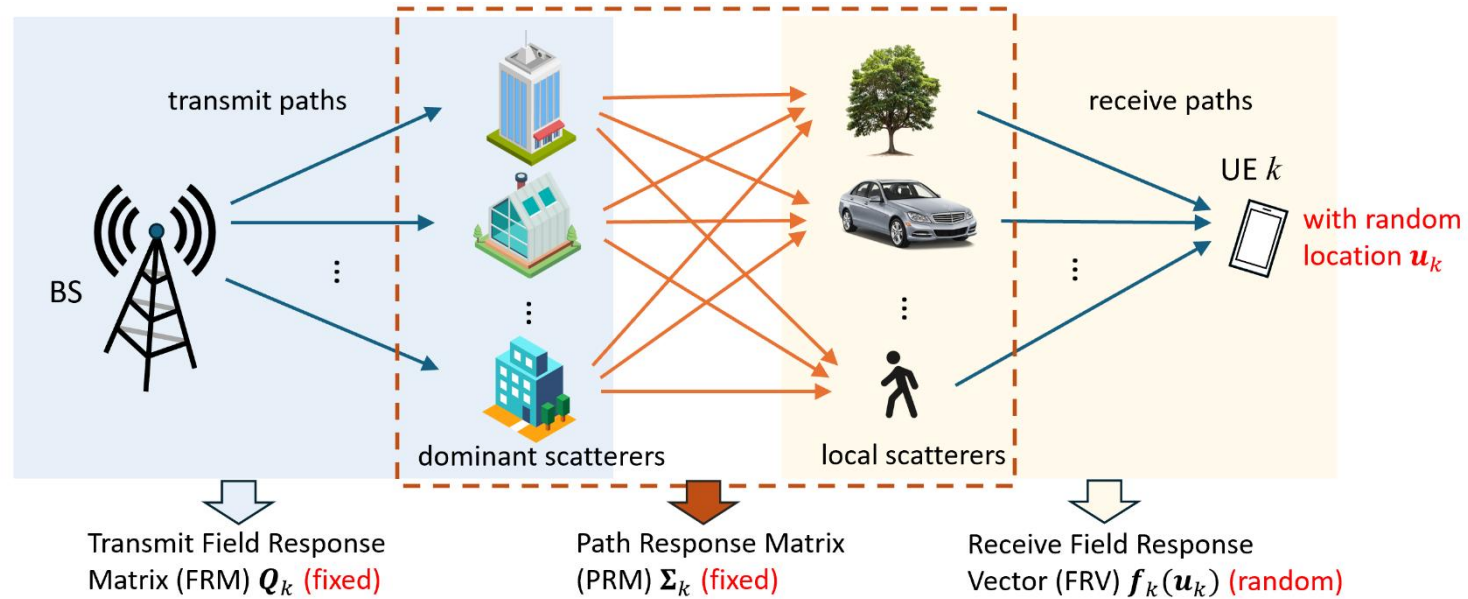


## System model:

- ❑ We consider a MU-MIMO communication system with  $N$  MAs at the BS and  $K$  single-antenna users.
- ❑ The position of the  $n$ th MA at the BS is denoted as  $\mathbf{r}_n = (x_n, y_n)$ .
- ❑ To enhance the system performance with less frequent antenna movements, a **two-timescale design** is proposed with the BS beamforming and antenna positions optimized based on the instantaneous and statistical CSI, respectively.

G. Yan, L. Zhu, and R. Zhang, "Movable antenna aided multiuser communications: antenna position optimization based on statistical channel information," IEEE Transactions on Communications, vol. 74, pp. 1793-1810, 2026.

# MA Optimization Based on Statistical CSI: Channel Model



Instantaneous channel vector for user  $k$ :  $\mathbf{h}_k = \mathbf{Q}_k^H \Sigma_k \mathbf{f}_k(\mathbf{u}_k)$

Statistical modeling:

$$\mathbf{h}_k = \mathbf{Q}_k^H \boldsymbol{\psi}_k, \quad \boldsymbol{\psi}_k \sim \mathcal{CN}(\mathbf{0}, \text{Diag}(\mathbf{b}_k))$$

mean power vector for all transmit paths (i.e., angular power spectrum)

Assuming moving UEs in rich scattering environments

Receive paths are combined at the UE with independent phase shifts

Decoupled and Gaussian transmit path response coefficients

Rayleigh fading for each UE with distinct channel covariance matrix defined by transmit FRM and angular power spectrum

# MA Optimization Based on Statistical CSI: Rate Maximization

- ❑ The receive signal-to-interference-and-noise ratio (SINR) for user  $k$ :

$$\gamma_k = \frac{|\mathbf{h}_k^H \mathbf{w}_k|^2}{\sigma^2 + \sum_{i \neq k} |\mathbf{h}_k^H \mathbf{w}_i|^2}$$

- ❑ To maximize the **ergodic sum rate** of all users, the optimization problem is formulated as

Expectation over channel realizations

Optimize antenna positions based on the statistical CSI

$$\begin{aligned} & \max_{\mathbf{x}, \mathbf{y}} \mathbb{E}_{\mathbf{H}} \left[ \max_{\mathbf{W}} \sum_{k=1}^K \log_2(1 + \gamma_k) \right], \\ & \text{s.t. } \text{tr}(\mathbf{W}^H \mathbf{W}) \leq P_T, \\ & |x_n| \leq \frac{S_x}{2}, |y_n| \leq \frac{S_y}{2}, \forall n, \\ & \|\mathbf{r}_n - \mathbf{r}_i\|_2 \geq \Delta, \forall n \neq i, \end{aligned}$$

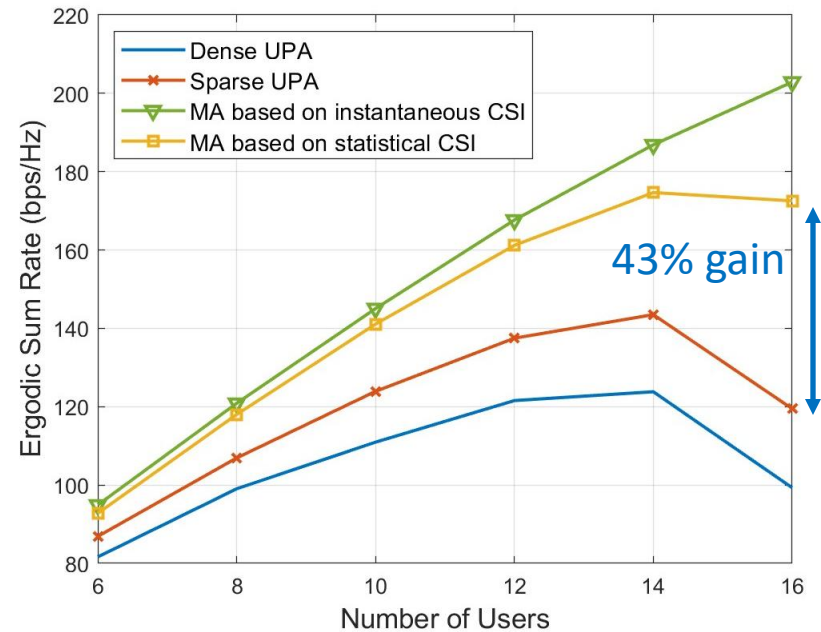
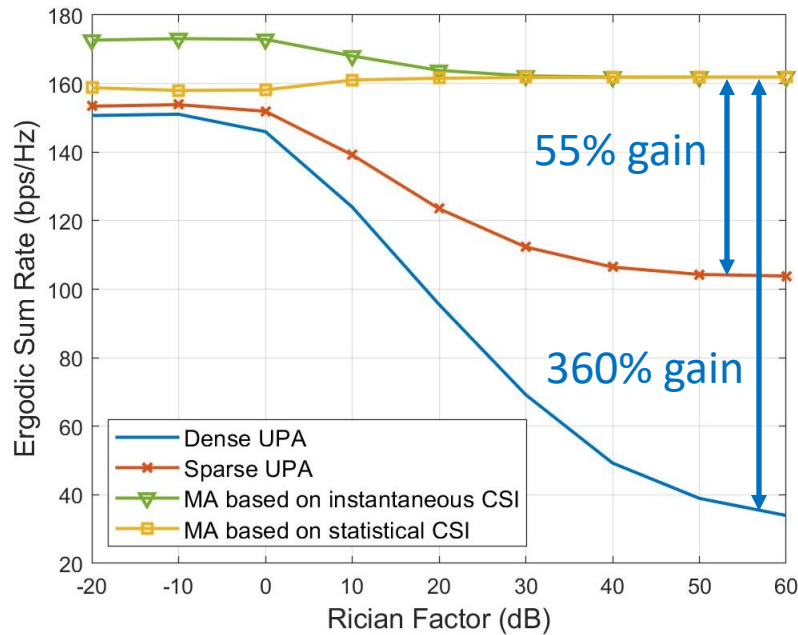
Instantaneous sum rate maximized by beamforming

Transmit power constraint for beamforming

Constraints on MA aperture & inter-antenna separations

- ❑ For simplicity and tractability of the problem, **ZF beamforming** is applied with water-filling power allocation, which is asymptotically optimal in high-SNR regions.
- ❑ For MA optimization, the constraints are incorporated into **log-barrier penalties** and **gradient ascent** is applied to maximize the surrogated objective function while shrinking the penalty coefficient to gradually approach the solution to the original problem.
- ❑ The gradient of the ergodic sum rate is computed based on **asymptotic analysis**.

# MA Optimization Based on Statistical CSI: Performance

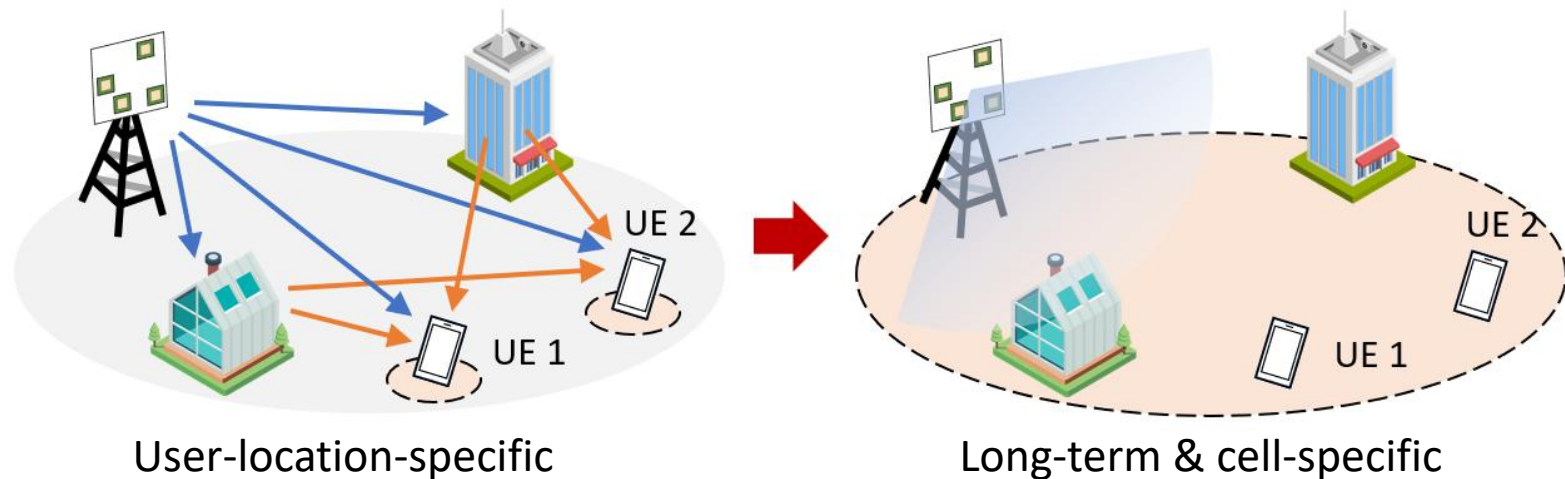


Ergodic Sum Rate versus the rician factor (left) and number of users (right) with randomly generated path AoDs and uniform power spectrum. Unless otherwise stated, there are 16 MAs at the BS, 12 users, and 6 transmit paths for each user.

## Observations:

- MA outperforms FPA (dense/sparse UPA) in terms of ergodic sum rate, especially with LoS-dominant channel and large number of users.
- MA optimized based on statistical CSI still effectively reduces channel correlations between users, achieving performance comparable to MA based on instantaneous CSI.

# Slow MA Design Based on Cell-Specific Channel Statistics



## System model:

- ❑ We consider a MU-MIMO communication system with  $N$  MAs at the BS serving multiple users across the cell.
- ❑ The position of the  $n$ th MA at the BS is denoted as  $\mathbf{r}_n = (x_n, y_n)$ .
- ❑ A **two-timescale design** is considered with the BS beamforming and antenna positions optimized based on the instantaneous and long-term channel statistics, respectively.
- ❑ Instead of small areas, mobile UEs are randomly distributed or moved across the cell over extended timescales, during which their number and statistical CSI vary as well.

G. Yan, L. Zhu, W. Ma, and R. Zhang, "Slow Movable Antenna System Design Based on Cell-Specific Long-Term Angular Power Spectrum," arXiv preprint arXiv:2605.12192, 2026.

# Slow MA Design Based on Cell-Specific Channel Statistics: Channel Model

- Insight: user channel in every subregion follows Gaussian distribution.



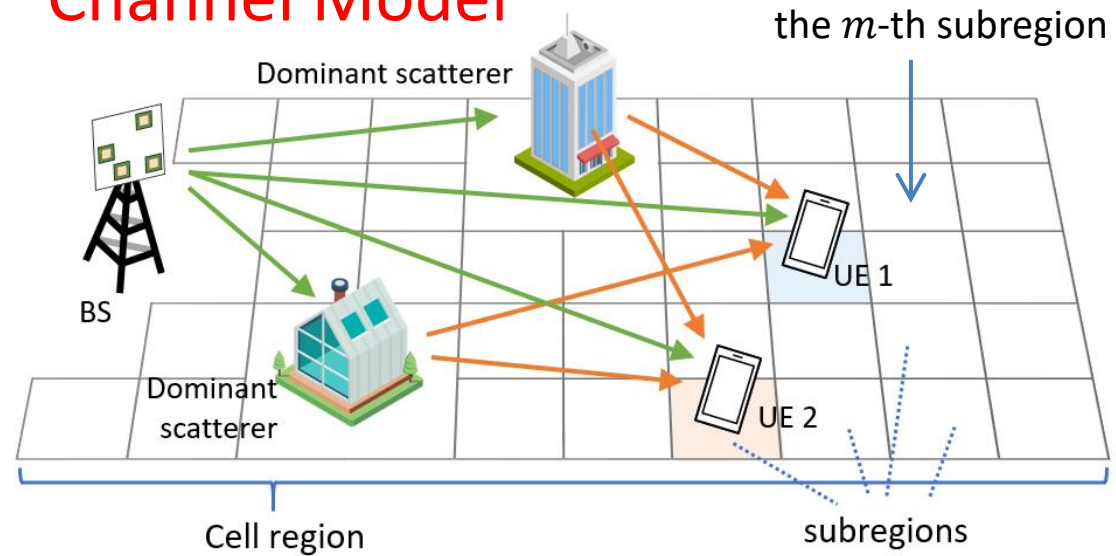
User channel within the cell follows a Gaussian-mixture distribution.



- Statistical channel for user  $k$ :  $\mathbf{h}_k \sim \mathcal{CN}(\mathbf{0}, \mathbf{G}_m)$ , w.p.  $\mu_m$ ,  $\forall k$

Covariance matrix for the  $m$ -th subregion

User probability for the  $m$ -th subregion



Scattering environment

Subregion-specific covariance matrices



Multi-user distribution across the cell

User distribution over subregions

User number distribution



Cell-specific Gaussian-mixture MU-MIMO Channel

# Slow MA Design Based on Cell-Specific Channel Statistics: Utility Maximization & Proposed Solution

- ❑ To maximize the **ergodic system utility**, the optimization problem is formulated as

Expectation over channel realizations  $\rightarrow$   $\max_{\mathbf{x}, \mathbf{y}} \mathbb{E}_{K, H} \left[ \max_{\mathbf{W}} g(\gamma; K) \right]$   $\leftarrow$  Instantaneous utility maximized by beamforming

Optimize antenna positions based on the statistical CSI  $\rightarrow$  s.t.  $\text{tr}(\mathbf{W}\mathbf{W}^H) \leq P_T$   $\leftarrow$  Transmit power constraint for beamforming

$|x_n| \leq \frac{S_x}{2}, |y_n| \leq \frac{S_y}{2}, \forall n,$   $\leftarrow$  Constraints on MA aperture & inter-antenna separations

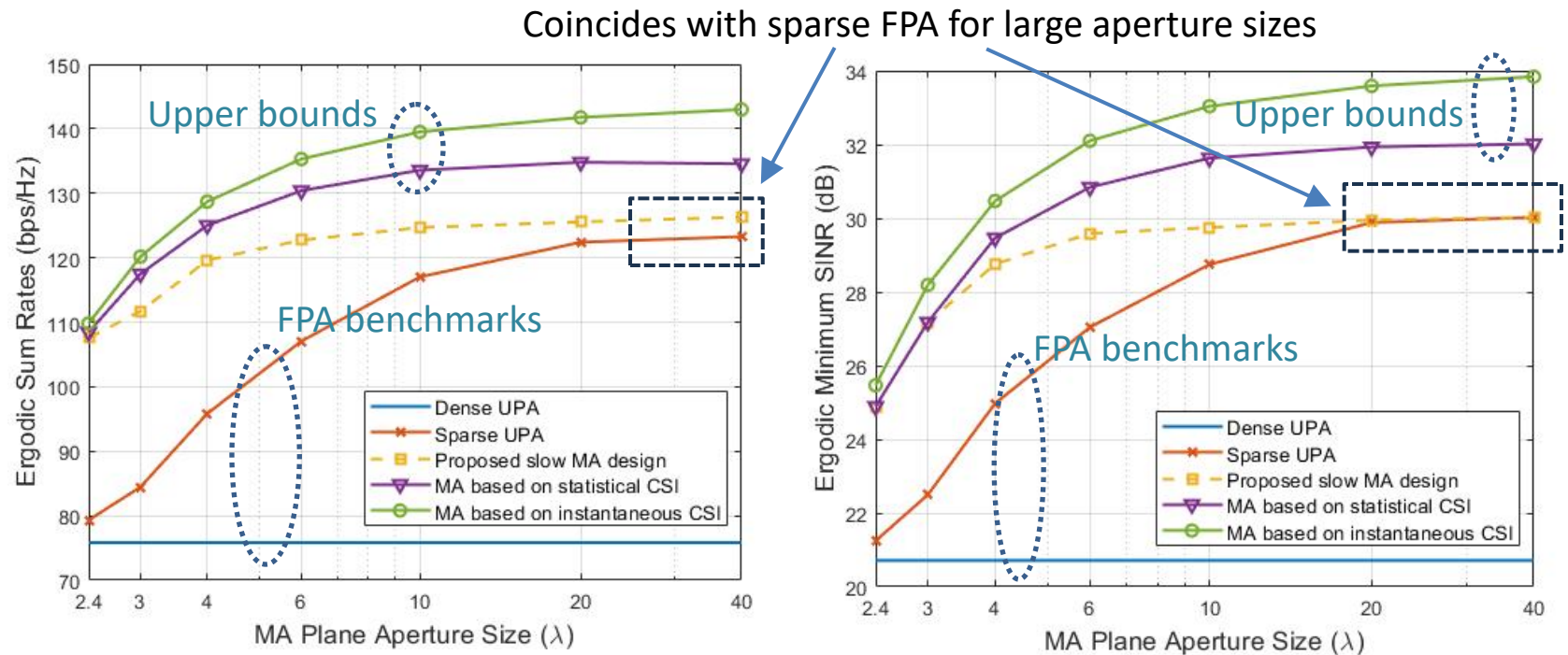
$\|\mathbf{r}_n - \mathbf{r}_i\|_2 \geq \Delta, \forall n \neq i,$   $\leftarrow$  Constraints on MA aperture & inter-antenna separations

- ❑ With **ZF beamforming** and **asymptotic approximation**, the ergodic utility performance can be intermediately maximized by incorporating constraints into **log-barrier penalties** and applying **gradient ascent** for the penalized surrogate objective.

Proposed **CEBAP** (covariance-eigenvalues-balancing antenna positions) Solution:

- Equalizes the eigenvalues of the average channel covariance matrix.
- Shown consistently effective to a broad range of utility functions, such as the weighted sum rate and weighted minimum SINR.
- Leverages the cell-specific **angular power spectrum** without requiring subregion-level channel statistics, thus further alleviating channel estimation burden.

# Slow MA Design Based on Cell-Specific Channel Statistics: Performance



Ergodic Sum Rate (left) and Ergodic Minimum SINR (right) versus the MA plane aperture size.

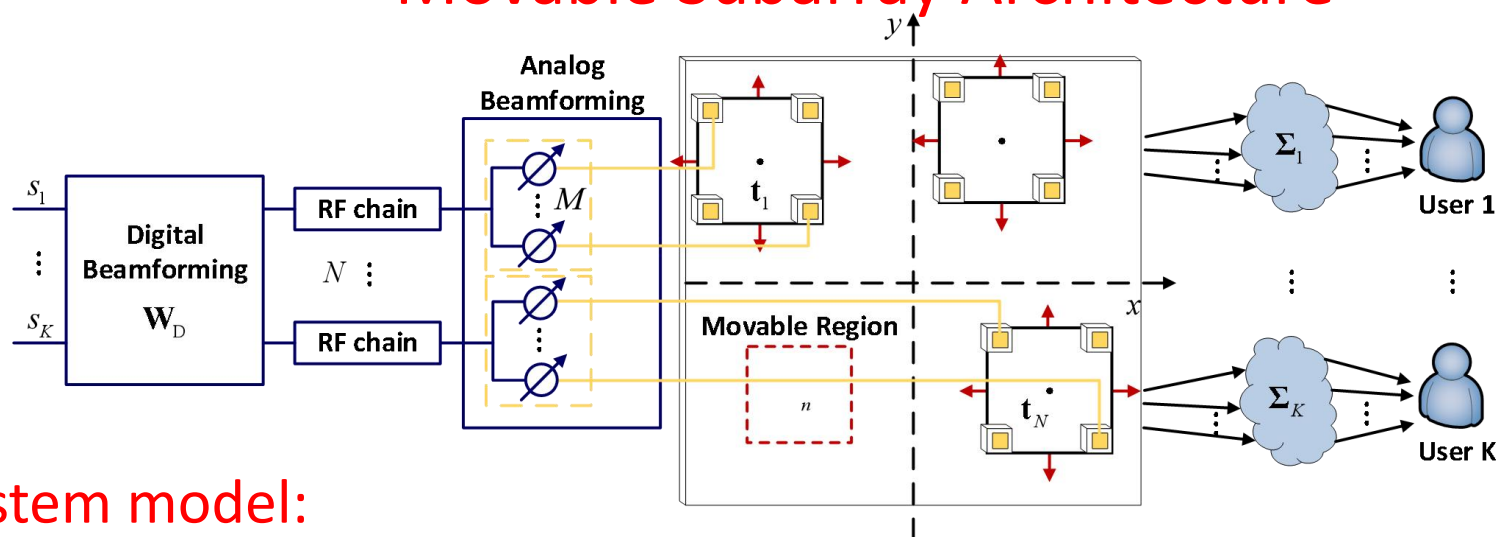
## Observations:

- ❑ Slow MA design closely approaches its upper bounds and significantly outperforms FPAs for small aperture sizes in terms of both **ergodic sum rate** and **minimum SINR**.
- ❑ Slow MA design performance coincides with sparse UPA as the aperture size is sufficiently large, where the **inter-user channel correlation** becomes negligible.

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# Movable Subarray Architecture



## System model:

- ❑ We consider a multiuser communication system that employs a sub-connected structure comprising  $N$  movable uniform planar arrays (UPAs) and  $K$  users
- ❑  $M$  antennas within each movable UPA move collectively
- ❑ Denote the coordinates of the central point of  $n$ th UPA by  $\mathbf{t}_n = [x_{t,n}, y_{t,n}]$  with its collections denoted by  $\mathbf{t}$
- ❑ For each UPA, the relative positions of the antennas with respect to the central point is denoted by  $\boldsymbol{\delta} = [\delta_1, \delta_2, \dots, \delta_M]$
- ❑ The channel matrix from  $n$ th UPA to  $k$ th UPA is denoted by  $\mathbf{h}_k(\mathbf{t}_n)$  with its collections denoted by  $\mathbf{h}_k(\mathbf{t})$

Y. Zhang, Y. Zhang, L. Zhu, S. Xiao, W. Tang, Y. C. Eldar, and R. Zhang, "Movable antenna-aided hybrid beamforming for multi-user communications," IEEE Transactions on Vehicular Technology, vol. 74, no. 6, pp. 9899-9903, June 2025.

# Movable Subarray-Aided Hybrid Beamforming

## Problem formulation:

- The achieve rate of  $k$ th user can be written as

$$R_k(\mathbf{t}) = \log_2 \left( 1 + \frac{|\mathbf{h}_k(\mathbf{t})^H \mathbf{W}_A \mathbf{w}_{D,k}|^2}{\sum_{k' \neq k} |\mathbf{h}_k(\mathbf{t})^H \mathbf{W}_A \mathbf{w}_{D,k'}|^2 + \sigma_k^2} \right)$$

- We aim to maximize the sum rate of all users jointly optimizing the central positions of UPAs  $\mathbf{t}$ , the analog beamformer  $\mathbf{W}_A = \text{blkdiag}(\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_N)$ , and the digital beamformer  $\mathbf{W}_D$ , the optimization problem is formulated as

Analog beamformer, digital  
beamformer, and transmit  
MA positions

$$\begin{aligned} \max_{\mathbf{W}_A, \mathbf{W}_D, \mathbf{t}} \quad & \sum_{k=1}^K R_k \\ \text{s.t.} \quad & \mathbf{t}_n \in \mathcal{C}_n, \quad n=1, 2, \dots, N, \\ & \|\mathbf{W}_A \mathbf{W}_D\|_F^2 \leq P, \\ & |[\mathbf{p}_n]_m| = 1, \quad n=1, 2, \dots, N, \quad m=1, 2, \dots, M. \end{aligned}$$

MA region constraints

Power budget constraint

Unit modulus constraints

## Solution:

Non-convex  
objective  
function with  
highly coupled  
variables



Equivalently  
reformulate  
original  
problem via  
fractional  
programming  
(FP) framework

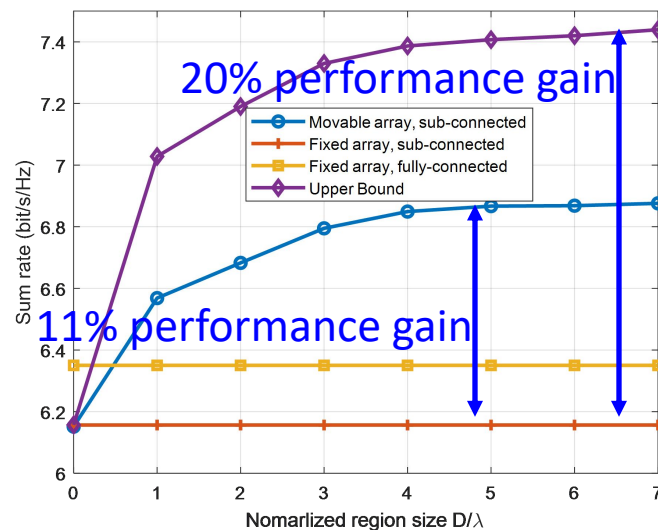


Obtain the  
closed-form  
solution of  
analog  
beamformer  
 $\mathbf{W}_A$  and digital  
beamformer  $\mathbf{W}_D$   
by AO

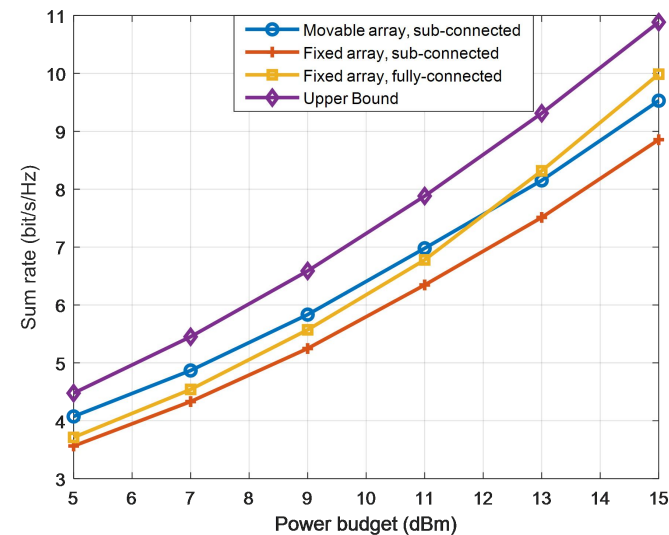


Optimize the  
MA position  
vector  $\mathbf{t}$  via  
gradient ascent  
method

# MA-Aided Hybrid Beamforming : Performance Comparison



Sum rate versus the normalized movable region size

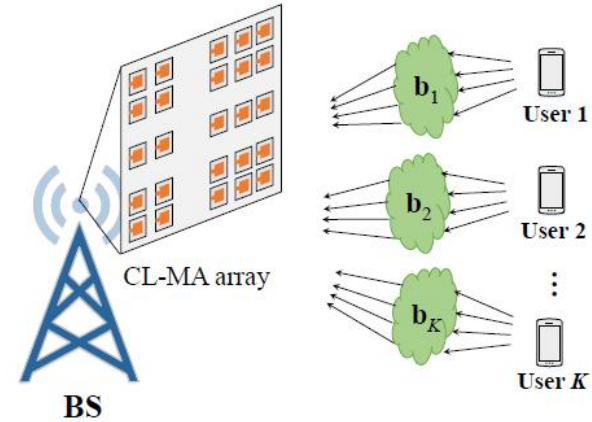
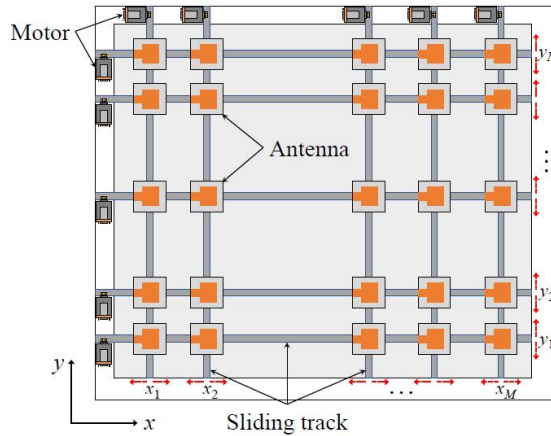


Sum rate versus power budget

## Observations:

- ❑ The performance gain from MA can compensate the performance loss of applying sub-connected structure in terms of sum-rate, and the performance gain increases with the movable region size
- ❑ MA-aided sub-connected structure can even outperform the fully-connected FPA for low SNR and large antenna moving region

# Cross-Linked Movable Antenna (CL-MA) Array



## System model:

- CL-MA array can realize collective antenna movement over both horizontal and vertical directions, requiring only  $M+N$  motors to drive  $MN$  MA elements
- Uplink transmission from  $K$  users to the BS:

$$\hat{\mathbf{s}} = \mathbf{W}^H \mathbf{H}(\mathbf{x}, \mathbf{y}) \mathbf{P}^{1/2} \mathbf{s} + \mathbf{W}^H \mathbf{z}$$

Horizontal APV

Vertical APV

- Uplink SINR for user  $k$ : 
$$\gamma_k = \frac{|\mathbf{w}_k^H \mathbf{h}_k(\mathbf{x}, \mathbf{y})|^2 p_k}{\sum_{q=1, q \neq k}^K |\mathbf{w}_k^H \mathbf{h}_q(\mathbf{x}, \mathbf{y})|^2 p_q + \|\mathbf{w}_k\|_2^2 \sigma^2}$$

L. Zhu, H. Sun, W. Ma, and R. Zhang, "Multiuser Communications Aided by Cross-Linked Movable Antenna Array: Architecture and Optimization," IEEE Transactions on Wireless Communications, vol. 25, pp. 6729-6744, Nov. 2025.

# CL-MA Array: Transmit Power Minimization

## Problem:

□ Minimize the uplink transmit power subject to a minimum rate requirement for each user:

$$\begin{aligned}
 & \min_{\mathbf{x}, \mathbf{y}, \mathbf{W}, \mathbf{p}} \sum_{k=1}^K p_k \\
 & \text{s.t.} \quad \log_2(1 + \gamma_k) \geq r_k, \quad 1 \leq k \leq K, \\
 & \quad p_k \geq 0, \quad 1 \leq k \leq K, \\
 & \quad 0 \leq x_m \leq x_{\max}, \quad 1 \leq m \leq M, \\
 & \quad x_{m+1} - x_m \geq d_{\min, x}, \quad 1 \leq m \leq M - 1, \\
 & \quad 0 \leq y_n \leq y_{\max}, \quad 1 \leq n \leq N, \\
 & \quad y_{n+1} - y_n \geq d_{\min, y}, \quad 1 \leq n \leq N - 1,
 \end{aligned}$$

Annotations:

- Minimum-rate requirement: points to  $\log_2(1 + \gamma_k) \geq r_k$
- MA region constraint: points to  $0 \leq x_m \leq x_{\max}$  and  $0 \leq y_n \leq y_{\max}$
- Inter-antenna distance constraint: points to  $x_{m+1} - x_m \geq d_{\min, x}$  and  $y_{n+1} - y_n \geq d_{\min, y}$

## Solution:

Express the transmit power as an explicit function of APVs based on ZF beamforming

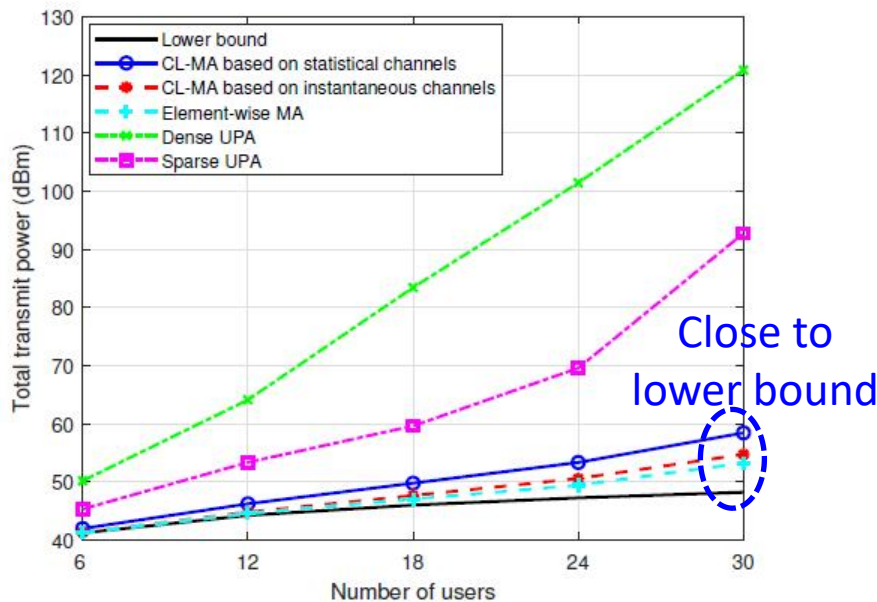


Discretize the antenna moving region with a sufficiently high resolution (assuming massive virtual antennas)

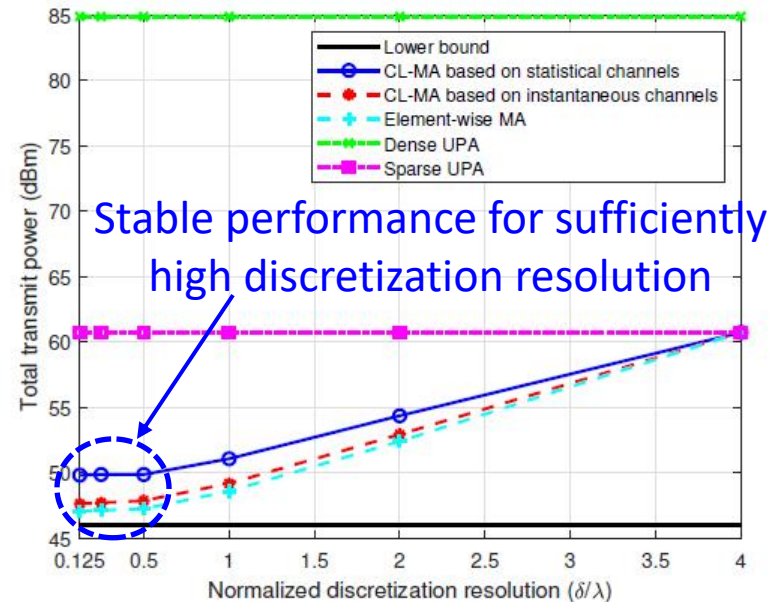


Conduct sequential elimination and successive refinement for APVs

# CL-MA Array: Performance Comparison



Total transmit power with the proposed and benchmark schemes versus the number of users

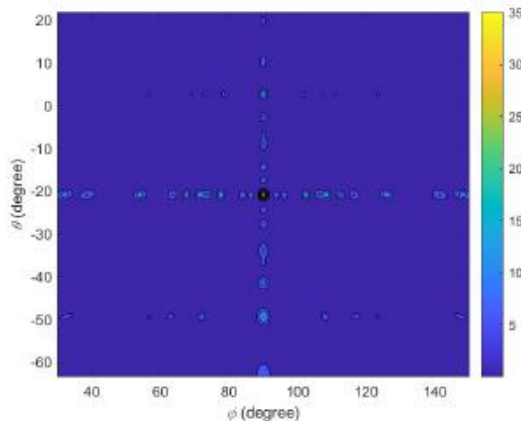


Total transmit power versus the resolution of discretizing antenna moving region

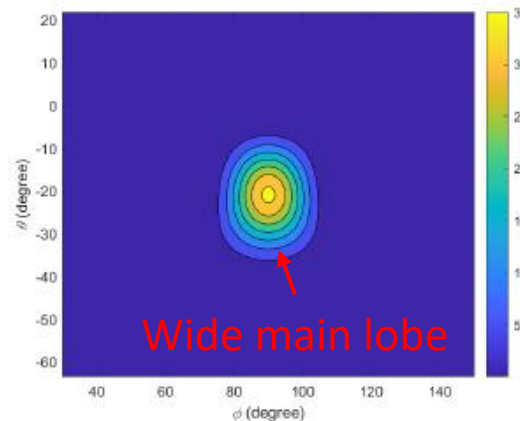
## Observations:

- ❑ Over 20 dB power-saving compared to dense/sparse UPA-based FPAs, especially for larger number of users and LoS-dominant channels
- ❑ CL-MA can achieve a performance close to conventional element-wise MA
- ❑ Discretization resolution of  $\lambda/4 \sim \lambda/2$  suffices to achieve near-optimal performance

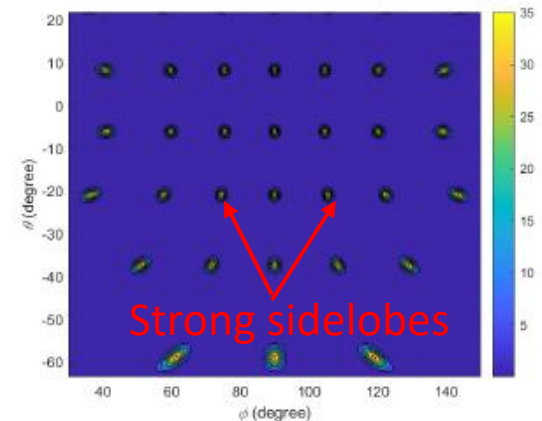
# CL-MA Array: Performance Comparison



(a) CL-MA array



(b) Dense UPA



(c) Sparse UPA

Beam patterns of different antenna arrays within the coverage sector of the BS

## Observations:

- ❑ The proposed CL-MA array can achieve **narrow main lobes** (maximum array aperture) and **mitigated sidelobes** (non-uniform array geometry), which help reduce multiuser channel correlation and thus enhance multiplexing performance

# Extremely Large-Scale Movable Antenna (XL-MA) Array

## Motivation:

- ❑ Flexible antenna repositioning over an extremely large region to achieve a larger virtual aperture than the compact MIMO, without need to increase the number of antenna elements and RF chains
- ❑ To reduce the overhead of frequent subarray relocation, their positions are optimized based on statistical channels



## System Overview:

- ❑ Uplink system with single-antenna users randomly distributed in a 3D region
- ❑ BS is equipped with  $N$  movable subarrays (each a UPA with  $M$  antennas)
- ❑ Each subarray is placed at one of  $N_0$  candidate positions within the XL-MA region

M. Fu, L. Zhu, and R. Zhang, "Extremely Large-Scale Movable Antenna-Enabled Multiuser Communications: Modeling and Optimization," IEEE Transactions on Wireless Communications, vol. 25, pp. 10290-10304, Jan. 2026.

# System Model

## Antenna placement matrix

$$[\Phi]_{n,\tilde{n}} = \begin{cases} 1, & \text{if } \tilde{n} = \mu(n), \\ 0, & \text{otherwise.} \end{cases} \quad \forall n \in \mathcal{N},$$

Selected position index  
for the  $n$ -th subarray

## Grid-based user distribution model:

$$\mathbb{P}(\alpha_k = 1) = \rho_k \quad \leftarrow \text{User density is the probability of a user in grid } k \text{ assigned to the RB}$$

## Spatially non-stationary channel model:

$$\tilde{\mathbf{h}}_k(\mathbf{r}_{\mu(n)}) = \underbrace{\xi_{\text{LoS},k}(\mathbf{r}_{\mu(n)})}_{\text{LoS visibility}} \underbrace{\sqrt{\beta_{\text{LoS},k}(\mathbf{r}_{\mu(n)})} e^{-j\psi_{k,\mu(n)}}}_{\text{LoS/NLoS path gains}} \underbrace{\mathbf{a}(\mathbf{u}_k(\mathbf{r}_{\mu(n)}))}_{\text{Array response vector}} + \tilde{\mathbf{h}}_{\text{NLoS},k}(\mathbf{r}_{\mu(n)})$$

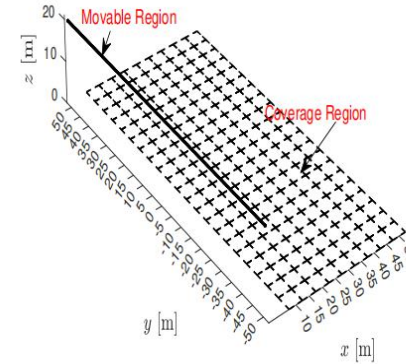
## Uplink signal over a typical RB

$$\mathbf{y} = (\Phi \otimes \mathbf{I}_M) \bar{\mathbf{H}} \mathbf{A} \mathbf{P}^{1/2} \mathbf{s} + \boldsymbol{\omega}$$

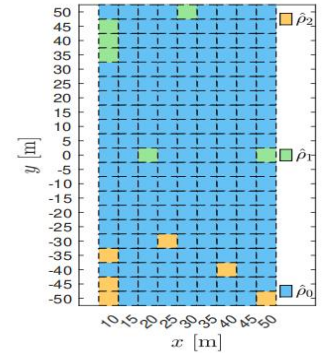
Antenna placement matrix

Virtual channel matrix from all grids  
to all candidate XL-MA positions

Diagonal grid-activation  
indicator matrix



(a) Movable and coverage regions.



(b) Grid-based user distribution.

# Expected Weighted Sum Rate Approximation

Expected weighted sum rate:

$$R_{\text{sum}}(\Phi) = \sum_{k=1}^K \rho_k \mathbb{E}_{\alpha_{-k}, \mathbf{H}} \{\log_2(1 + \gamma_k)\}$$

random grid-activation indicators
random channel matrix

Closed-form approximation of the expected achievable rates: MRC receiver

$$\tilde{R}_k^{\text{MR}}(\Phi) = \log_2 \left( 1 + \frac{\bar{P}_k \left( M^2 (\mathbf{1}_N^T \Phi \bar{\beta}_k)^2 + M \mathbf{1}_N^T \Phi (\bar{\beta}_k^{[2]} \circ \bar{\mathbf{f}}_k) \right)}{\mathbf{1}_N^T \Phi \left( \sum_{i \neq k} \bar{P}_i \rho_i (\bar{\beta}_k \circ \bar{\beta}_i \circ (\bar{\varphi}_{k,i} \circ \bar{\mathbf{g}}_{k,i} + \bar{\mathbf{q}}_{k,i})) + M \bar{\beta}_k \right)} \right)$$

large-scale path gains including LoS indicator,  
LoS/NLoS path gains
User channel correlation

## Insights

Optimized placement boosts desired signal power (**high path gains**) and reduces interference (**low user channel correlation**)

# Optimizing Antenna Placement Matrix

## Problem formulation:

- We aim to maximize the **expected weighted sum rate** under MRC by determining the optimal positions of  $N$  MA subarrays, under practical constraints. Accordingly, we formulate the optimization problem as

$$\text{maximize}_{\Phi} \quad \sum_{k=1}^K \rho_k \tilde{R}_k^{\text{MR}}(\Phi) \quad \leftarrow \quad \text{Approximated expected weighted sum rate}$$

$$\text{subject to} \quad [\Phi]_{n,\tilde{n}} \in \{0, 1\}, \quad \forall n \in \mathcal{N}, \quad \forall \tilde{n} \in \mathcal{N}_0,$$

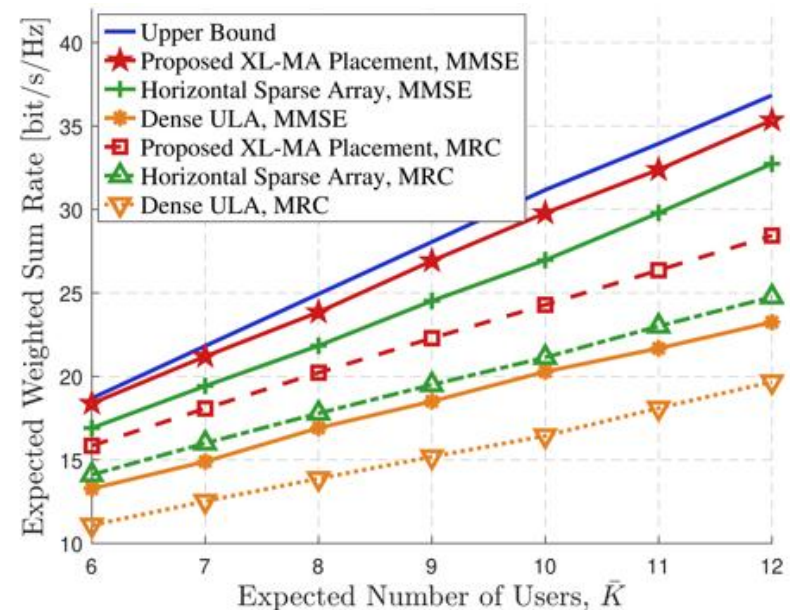
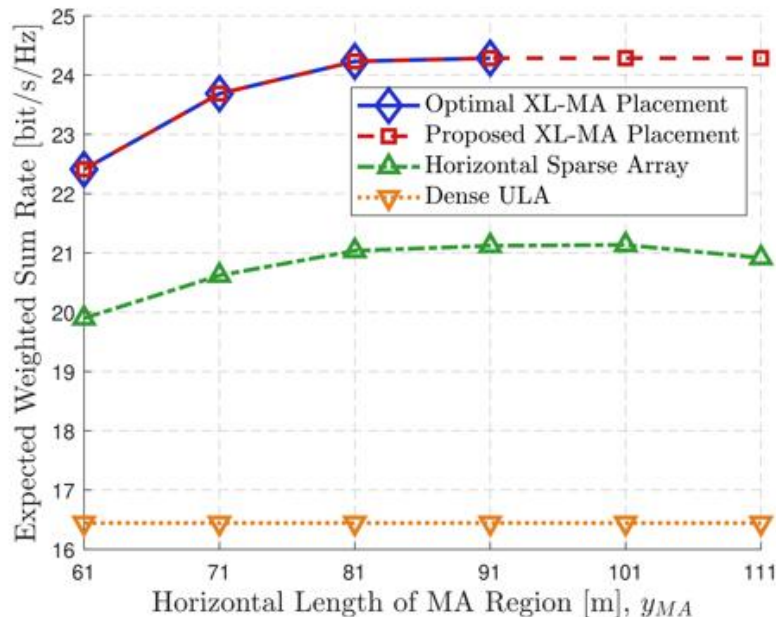
$$\text{Each position can host at most one subarray.} \quad \rightarrow \quad \mathbf{1}_N^T \Phi \leq \mathbf{1}_{N_0}^T,$$

$$\Phi \mathbf{1}_{N_0} = \mathbf{1}_N \quad \leftarrow \quad \text{Each subarray selects exactly one position}$$

## Solution:

- Reformulation into **reduced-dimension** vector form  $\chi^T \triangleq \mathbf{1}_N^T \Phi$
- Propose **successive replacement algorithm** with a **polynomial** complexity

# Performance comparison under full LoS visibility

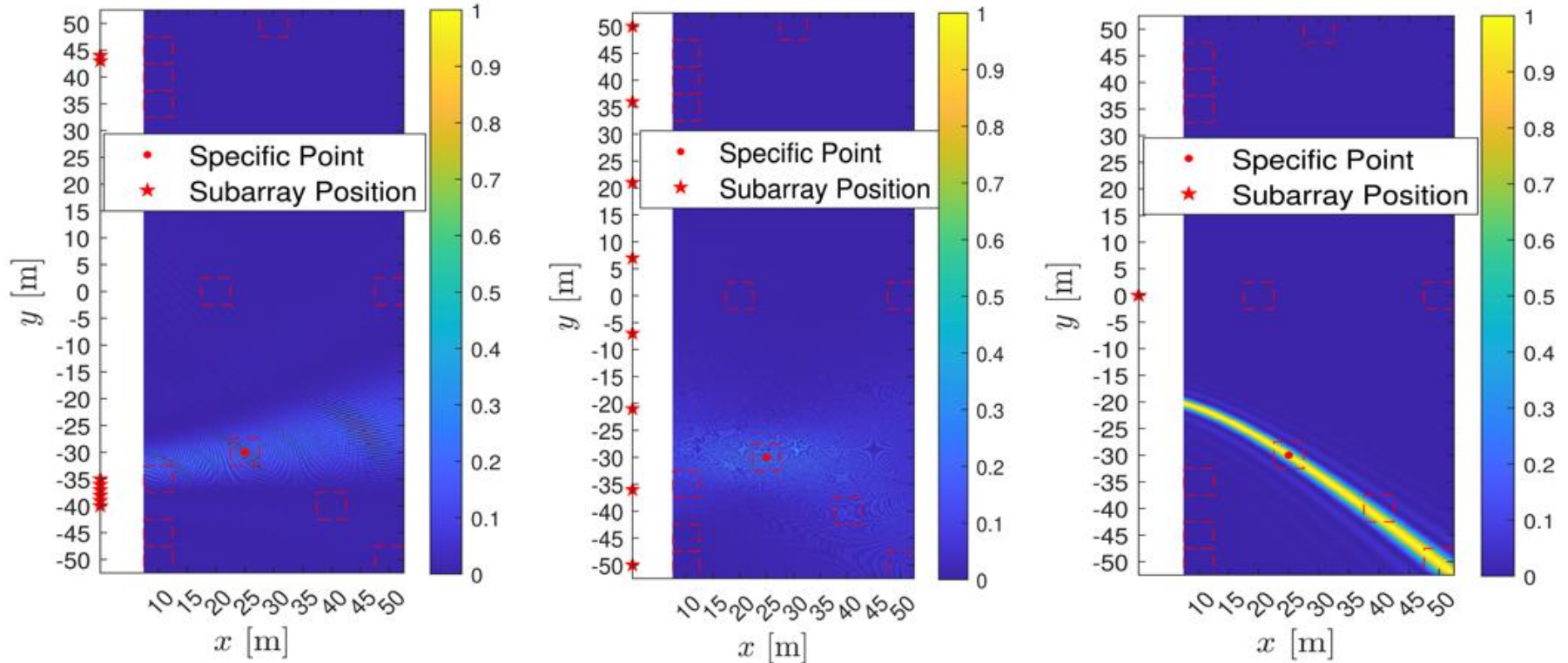


Region size (left) and Number of average users (right) under 1D moving and 2D coverage regions

## Observations:

- ❑ Proposed low-complexity algorithm achieves near-optimal performance compared to exhaustive search
- ❑ XL-MA placement significantly outperforms FPA baselines

# Simulations: Channel Correlation Maps

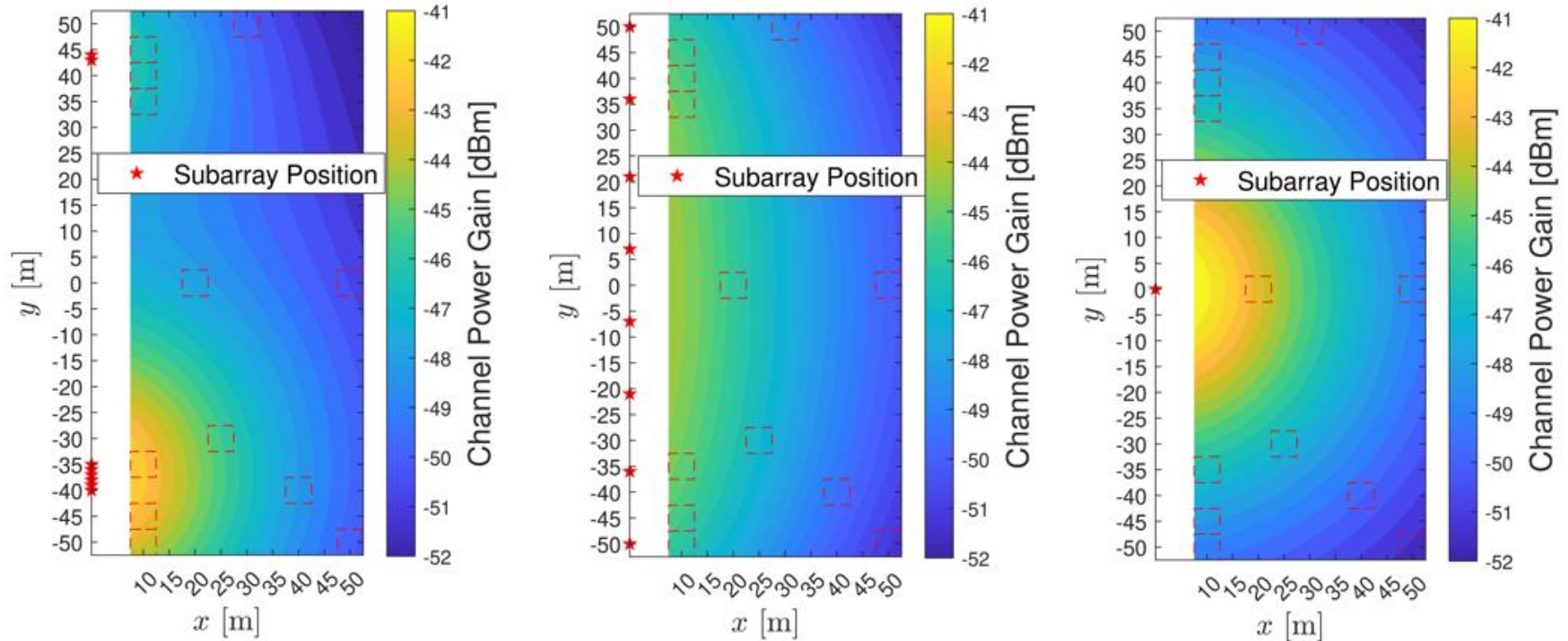


Proposed XL-MA Placement (left), horizontal sparse array (middle), and dense ULA (right)

## Observations:

- ❑ The proposed XL-MA placement shows **low channel correlation** near the target grid and **negligible correlation** with other grids with non-zero user densities/probabilities (dashed red boxes)

# Simulations: Power Gain Maps

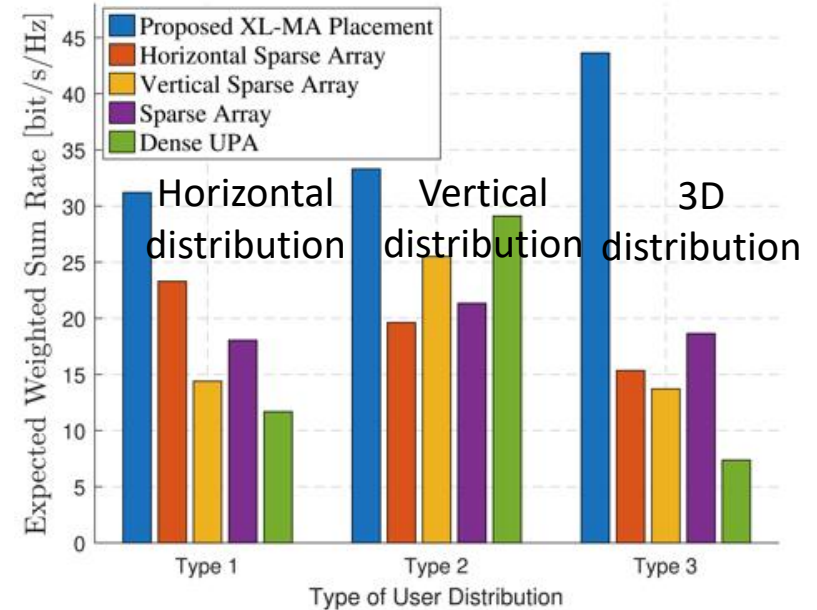
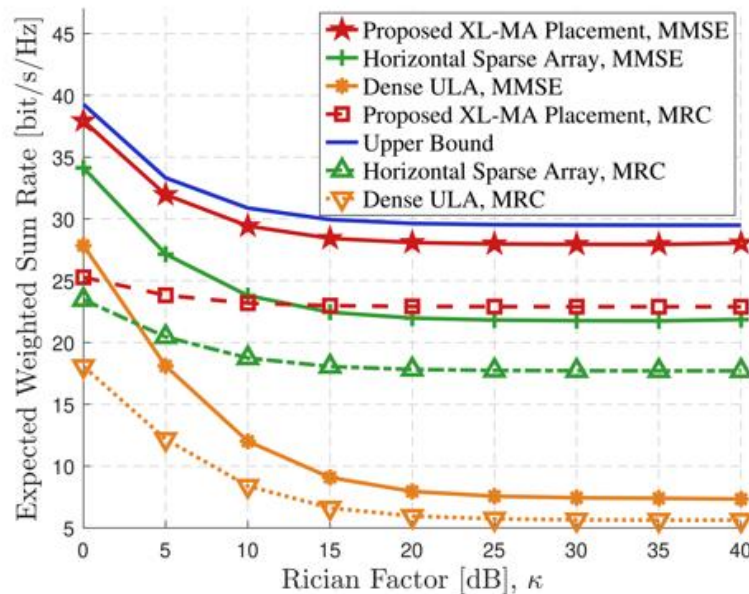


Proposed XL-MA Placement (left), horizontal sparse array (middle), and dense ULA (right)

## Observations:

- ❑ The proposed XL-MA placement forms a non-uniform sparse geometry, predominantly concentrating channel power gain on the major hotspot grids

# Performance comparison under partial LoS visibility

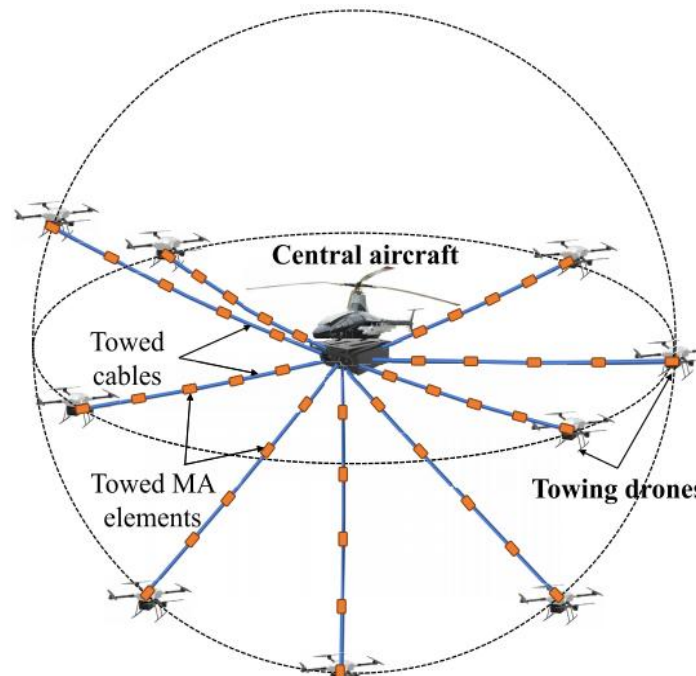


Varying Rician factor (left) and different user distribution (right)

## Observations:

- ❑ For LoS-dominant channels, the proposed XL-MA placement achieves higher performance gain over FPAs
- ❑ The proposed XL-MA placement outperforms all FPA benchmarks, especially under 3D non-uniform user distributions (Type 3)

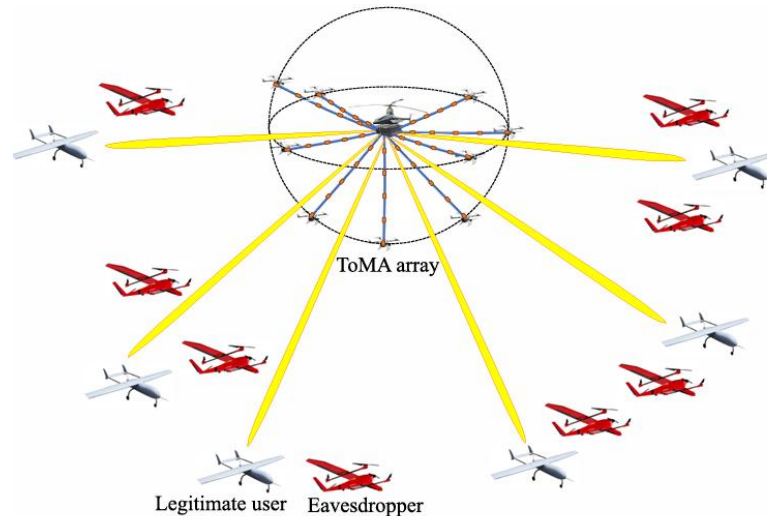
# Towed Movable Antenna (ToMA) Array Architecture



- ❑  $M$  flexible cables with length  $L$  are attached to the central aircraft
- ❑ Each flexible cable is towed by a drone
- ❑  $N$  antenna elements are uniformly distributed along each cable, forming a ULA
- ❑ Flexible array geometry reconfiguration via location adjustment of towing drones

L. Zhu, H. Mao, W. Ma, Z. Xiao, J. Zhang, and R. Zhang, "Towed Movable Antenna (ToMA) Array for Ultra Secure Airborne Communications," IEEE Journal On Selected Areas In Communications, vol. 44, pp. 3766-3781, Mar. 2026.

# System Model



- ❑ ToMA array at the central craft transmits secrecy messages to  $K$  legitimate users, while  $I$  hostile eavesdroppers aim to intercept these information.

- ❑ The coordinate of the  $m$ -th towing drone is denoted as

$$\mathbf{t}_m = [x_m, y_m, z_m]^T$$

- ❑ The coordinate of the  $n$ -th antenna element on the  $m$ -th towed cable is given by

$$\mathbf{t}_{m,n} = \frac{n}{N} \mathbf{t}_m$$

- ❑ The signals received at the users and the eavesdroppers can be respectively expressed as

$$\begin{aligned} \mathbf{y}_u &= \mathbf{H}(\tilde{\mathbf{t}})^H \mathbf{W} \mathbf{s} + \mathbf{n}_u, \\ \mathbf{y}_e &= \mathbf{G}(\tilde{\mathbf{t}})^H \mathbf{W} \mathbf{s} + \mathbf{n}_e. \end{aligned}$$

Channel matrix Beamforming matrix transmitted signal Noise

## Channel Model

- Assume **the near-field channel condition** between the ToMA array and users and eavesdropper, since the aperture size of the ToMA array is extremely large
- The array response vector under uniform spherical wave model is given by

$$\mathbf{a}(\tilde{\mathbf{t}}, \mathbf{r}) = \left[ e^{j \frac{2\pi}{\lambda} \|\mathbf{t}_{m,n} - \mathbf{r}\|} \right]_{1 \leq m \leq M, 1 \leq n \leq N}^T \in \mathbb{C}^{MN \times 1}$$

- The channel vectors for user  $k$  and eavesdropper  $i$  are respectively given by

$$\begin{aligned} \mathbf{h}_k(\tilde{\mathbf{t}}) &= \alpha_k \mathbf{a}(\tilde{\mathbf{t}}, \mathbf{r}_{u,k}) \in \mathbb{C}^{MN \times 1}, \quad 1 \leq k \leq K, \\ \mathbf{g}_i(\tilde{\mathbf{t}}) &= \beta_i \mathbf{a}(\tilde{\mathbf{t}}, \mathbf{r}_{e,i}) \in \mathbb{C}^{MN \times 1}, \quad 1 \leq i \leq I, \end{aligned}$$

- The channel matrices for all  $K$  users and all  $I$  eavesdroppers are denoted as

$$\begin{aligned} \mathbf{H}(\tilde{\mathbf{t}}) &= [\mathbf{h}_1(\tilde{\mathbf{t}}), \mathbf{h}_2(\tilde{\mathbf{t}}), \dots, \mathbf{h}_K(\tilde{\mathbf{t}})] \\ \mathbf{G}(\tilde{\mathbf{t}}) &= [\mathbf{g}_1(\tilde{\mathbf{t}}), \mathbf{g}_2(\tilde{\mathbf{t}}), \dots, \mathbf{g}_I(\tilde{\mathbf{t}})] \end{aligned}$$

## Problem Formulation

- To guarantee ultra secure and covert transmission, the **transmit beamforming matrix** is designed based on **the ZF criterion** with the instantaneous channels/locations of the users and eavesdroppers:

$$\mathbf{W}(\tilde{\mathbf{t}}) = \sqrt{P} \frac{\bar{\mathbf{W}}(\tilde{\mathbf{t}})}{\|\bar{\mathbf{W}}(\tilde{\mathbf{t}})\|_F},$$

$$\bar{\mathbf{W}}(\tilde{\mathbf{t}}) = [\mathbf{H}(\tilde{\mathbf{t}}), \mathbf{G}(\tilde{\mathbf{t}})]([\mathbf{H}(\tilde{\mathbf{t}}), \mathbf{G}(\tilde{\mathbf{t}})]^H [\mathbf{H}(\tilde{\mathbf{t}}), \mathbf{G}(\tilde{\mathbf{t}})])^{-1}]_{:,1:K}$$

- The corresponding achievable rate of each user is given by

$$r(\tilde{\mathbf{t}}) = \log_2 \left( 1 + \frac{P}{\|\bar{\mathbf{W}}(\tilde{\mathbf{t}})\|_F^2 \sigma^2} \right)$$

- Maximize the ergodic achievable rate of the users by jointly optimizing the APV of the ToMA array

$$\max_{\tilde{\mathbf{t}}} \mathbb{E}\{r(\tilde{\mathbf{t}})\}$$

$$\text{s.t. } \|\mathbf{t}_m\| = L, \quad 1 \leq m \leq M,$$

$$\|\mathbf{t}_m - \mathbf{t}_{\hat{m}}\| \geq D, \quad 1 \leq m \neq \hat{m} \leq M,$$

Each towed ULA cable remains  
in its fully extended state

Minimum distance between  
any two towing drones

# Performance Analysis

- ❑ Considering the simple case of a single user (i.e.,  $K = 1$ ) and a single eavesdropper (i.e.,  $I = 1$ ) with deterministic positions, and a single towing drone, the original objective is reduced to

$$\min_{\tilde{\mathbf{t}}} |\mathbf{a}(\tilde{\mathbf{t}}, \mathbf{r}_u)^H \mathbf{a}(\tilde{\mathbf{t}}, \mathbf{r}_e)| \quad \leftarrow \text{minimize the correlation of the array response vectors for the user and eavesdropper}$$

- ❑ **Far-field condition:** The user and eavesdropper are located in the far-field region of the ToMA array

$$\min_{\tilde{\mathbf{t}}} f_{\text{ff}}(\tilde{\mathbf{t}}) = \begin{cases} 0, & \text{if } \|\hat{\mathbf{r}}_u - \hat{\mathbf{r}}_e\| L \geq \lambda, \\ F_{\text{ff}}(L), & \text{if } \|\hat{\mathbf{r}}_u - \hat{\mathbf{r}}_e\| L < \lambda, \\ N, & \text{if } \|\hat{\mathbf{r}}_u - \hat{\mathbf{r}}_e\| = 0, \end{cases}$$

➤ **Sufficiently long ULA cable:** The channel vectors of the user and eavesdropper can be **orthogonal** via adjusting the location of towing drone

$$\mathbf{t}_1 = \pm L \frac{\hat{\mathbf{r}}_u - \hat{\mathbf{r}}_e}{\|\hat{\mathbf{r}}_u - \hat{\mathbf{r}}_e\|}$$

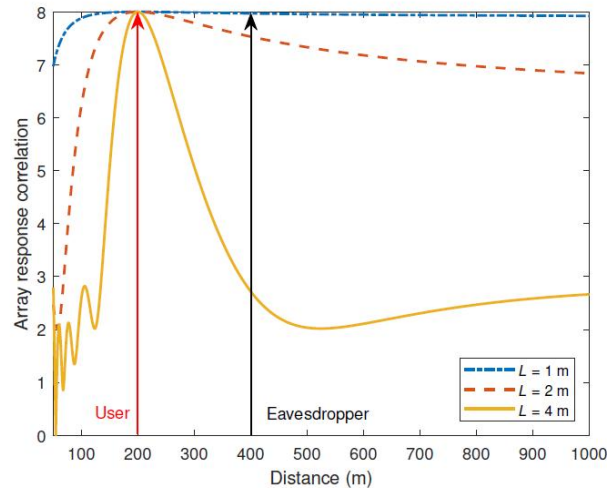
- **Limited length of ULA cable:** The minimum array response correlation is achieved if and only if the boresight of the ULA cable is aligned with the **angular bisector** between the user and eavesdropper directions
- Increasing  $L$  leads to enlarged effective array aperture, thus improving **angular resolution**

# Performance Analysis

- ❑ **Same-direction condition:** The user and eavesdropper are located in the same direction to the center of the ToMA array

$$\min_{\tilde{\mathbf{t}}} f_{\text{sd}}(\tilde{\mathbf{t}}) = \begin{cases} F_{\text{sd}}(L), & \text{if } \left( \frac{1}{\|\mathbf{r}_e\|} - \frac{1}{\|\mathbf{r}_u\|} \right) L^2 < \lambda, \\ N, & \text{if } \|\mathbf{r}_u\| - \|\mathbf{r}_e\| = 0, \end{cases} \quad \longleftrightarrow \quad \hat{\mathbf{r}}^T \mathbf{t}_1 = 0$$

- The towed ULA should be oriented perpendicular to the wave direction to **maximize the effective array aperture**
- Increasing the ULA cable length can effectively enhance the secure communication performance.



# Performance Optimization

- Considering the general case involving multiple towed ULAs, the optimization problem is given by

$$\begin{aligned} \max_{\tilde{\mathbf{t}}} \quad & \mathbb{E}\{r(\tilde{\mathbf{t}})\} \\ \text{s.t.} \quad & \|\mathbf{t}_m\| = L, \quad 1 \leq m \leq M, \\ & \|\mathbf{t}_m - \mathbf{t}_{\hat{m}}\| \geq D, \quad 1 \leq m \neq \hat{m} \leq M, \end{aligned}$$

Constraint on the spherical manifold

- We develop a **Riemannian manifold optimization** algorithm with **Monte Carlo method** approximating the objective function, where the Euclidean gradient is numerically calculated

$$\mathbb{E}\{r(\tilde{\mathbf{t}})\} \approx \frac{1}{Q} \sum_{q=1}^Q r_q(\tilde{\mathbf{t}}) \triangleq \tilde{r}(\tilde{\mathbf{t}})$$

$$\begin{aligned} [\nabla_{\mathbf{t}} \tilde{r}_m(\mathbf{t})]_i &= \frac{\partial \tilde{r}_m(\mathbf{t})}{\partial [\mathbf{t}]_i} \\ &= \lim_{\delta \rightarrow 0} \frac{\tilde{r}_m(\mathbf{t} + \delta \mathbf{e}_3^i) - \tilde{r}_m(\mathbf{t})}{\delta}, \quad 1 \leq i \leq 3, \end{aligned}$$

- The **minimum inter-cable distance constraint** is satisfied with the **backtracking line search**

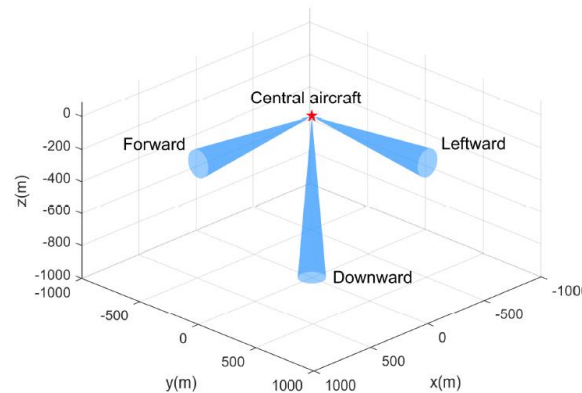
$$\tilde{r}_m(\text{Retr}_{\mathbf{t}^{(j)}}(\tau^{(j)} \boldsymbol{\mu}^{(j)})) \geq \tilde{r}_m(\mathbf{t}^{(j)}) + \xi \tau^{(j)} \|\text{grad}_{\mathbf{t}^{(j)}} \tilde{r}_m\|$$

Stepsize

# Simulation Setups

## ❑ Parameter settings:

- ✓ Carrier frequency: 10 GHz
- ✓ Noise power: -90 dBm
- ✓ Number of towed ULAs:  $M=6$
- ✓ Number of antennas *per ULA* :  $N=6$
- ✓ Numbers of users and eavesdroppers:  $K=10, I=10$
- ✓ The minimum inter-drone distance is 0.5 m
- ✓ Users and eavesdroppers are randomly distributed within three conical regions pointing forward (x-axis), leftward (y-axis), and downward ( $-z$ -axis)
- ✓ Each cone has a vertex angle of  $10^\circ$  , and the distance to the central aircraft ranges from 100 m to 1000 m.

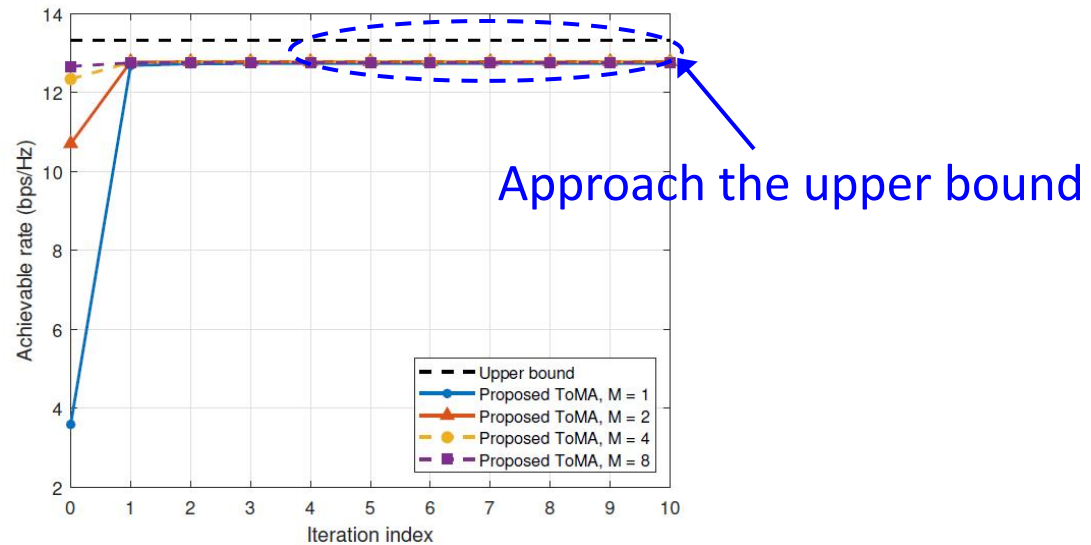


# Benchmark Schemes

## □ Benchmark schemes:

- ✓ **Horizontal placement**: The towed ULAs are all placed on the horizontal plane (i.e., x-O-y plane), with an equal intersection angle between any two adjacent ULAs.
- ✓ **Vertical placement**: The towed ULAs are all placed on the *vertical* plane (i.e., x-O-y plane), with an equal intersection angle between any two adjacent ULAs.
- ✓ **Hybrid placement**: Half of the towed ULAs are placed on the horizontal plane and the remaining towed ULAs are placed on the vertical plane, with an equal intersection angle between any two adjacent ULAs on each plane.
- ✓ **FPA-Dense UPA**: The antenna elements form a uniform planar array (UPA) of size  $M \times N$ , with the inter-antenna spacing given by  $\lambda/2$ .
- ✓ **FPA-Sparse UPA**: The antenna elements form an UPA of size  $M \times N$ , with the inter-antenna spacing given by  $2\lambda$ .

# Performance Evaluation: Algorithm Convergence

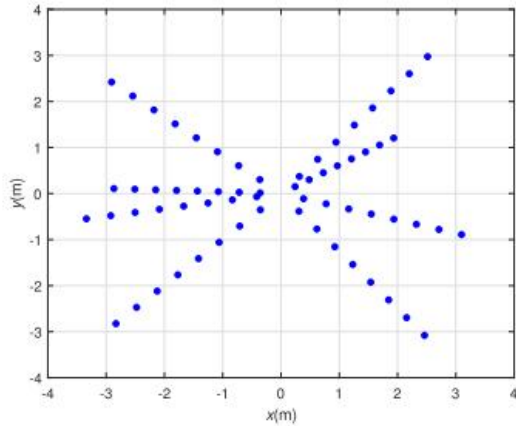


Approach the upper bound

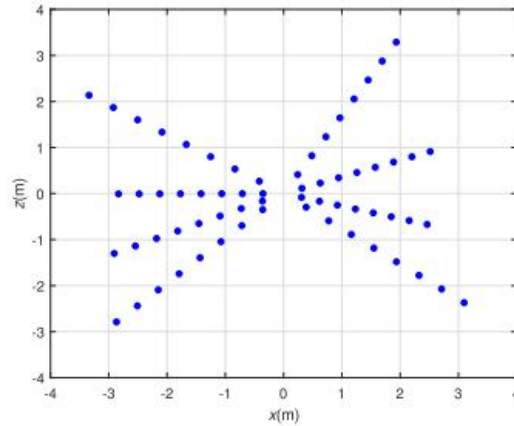
## Observations:

- ❑ For different numbers of towed ULAs,  $M$ , the algorithm consistently exhibits fast convergence, and closely approaches the upper bound on the achievable rate.

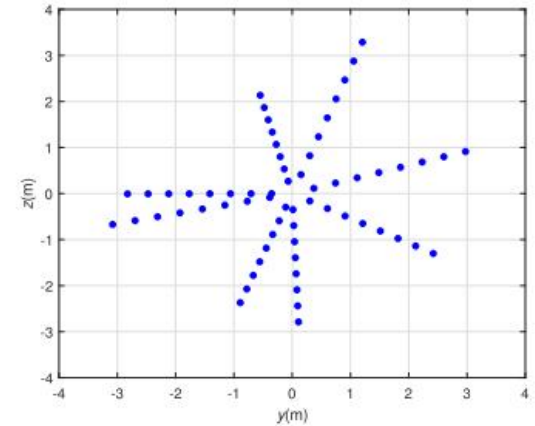
# Performance Evaluation: Optimized Antenna Positions



(a)  $x$ - $O$ - $y$  plane



(b)  $x$ - $O$ - $z$  plane

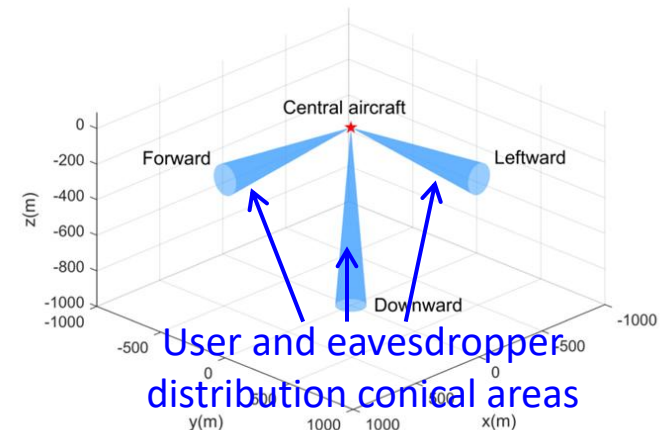


(c)  $y$ - $O$ - $z$  plane

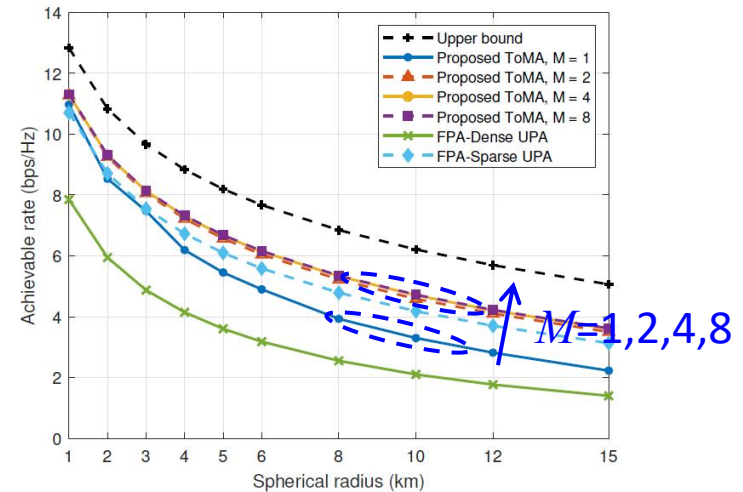
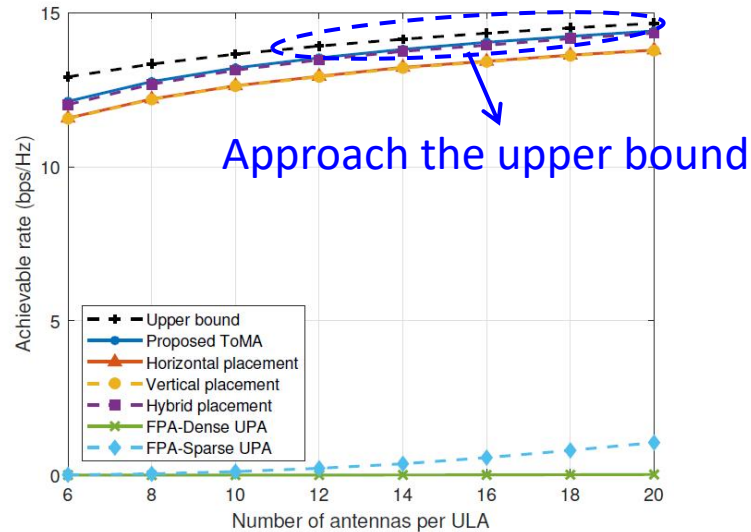
The projection of optimized antenna positions on different planes

## Observations:

- The projections of the array geometry onto the three planes exhibit large and balanced apertures, significantly reducing array response correlation between users and eavesdroppers



# Performance Evaluation



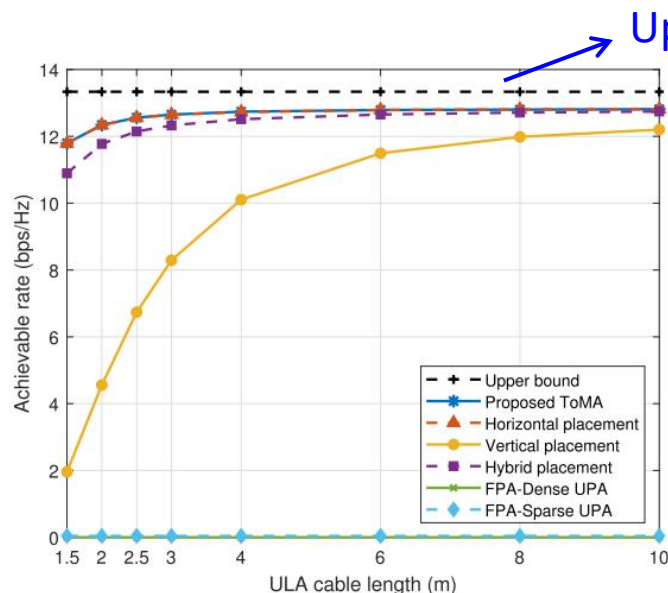
Achievable rate with increasing number of antennas per ULA

Achievable rate with increasing spherical radius

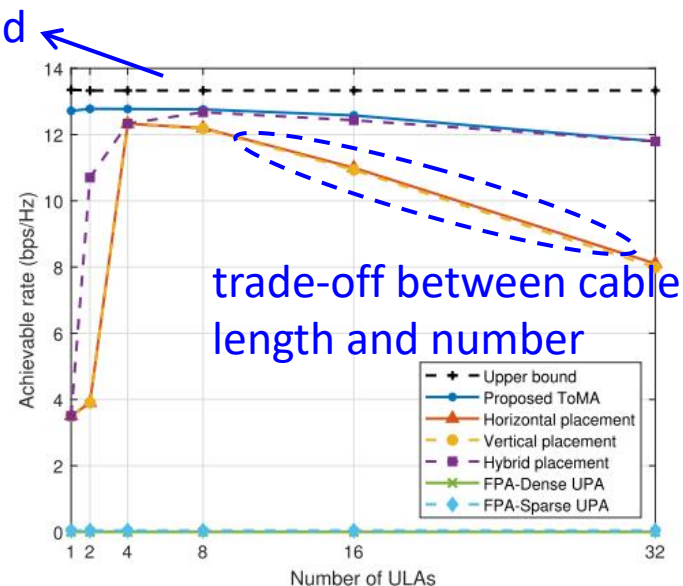
## Observations:

- ❑ Conventional FPA schemes with either dense or sparse array layouts yield significantly lower achievable rates, since FPA arrays with limited apertures fail to effectively distinguish spatially close users and eavesdroppers
- ❑ Multiple towed ULAs enable well-balanced effective apertures across different directions, thereby enhancing performance compared to a single ULA.

# Performance Evaluation



Achievable rate with increasing cable length



Achievable rate with increasing number of ULAs while the total cable length is fixed

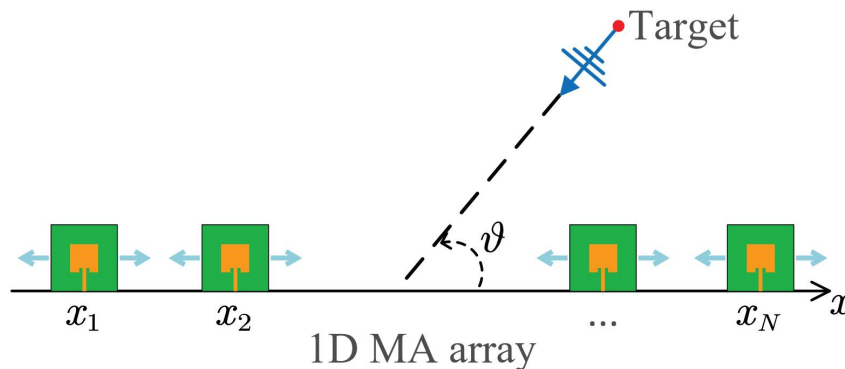
## Observations:

- ❑ ToMA array exhibits **increasing rate performance** as the length of each towed ULA cable increases, benefiting from the **enlarged array aperture**
- ❑ As the number of cables continues to increase, the rate performance begins to **decline**, because, under the **fixed total cable length**, increasing the number of cables **reduces the length of each ULA** and **shrinks the overall effective aperture**

# Outline

- ❑ Introduction of Movable Antenna
- ❑ MA System Design Based on Channel Statistics
- ❑ Efficient MA Architectures
- ❑ MA for Wireless Sensing
- ❑ Conclusions and Future Directions

# MA-Enhanced Wireless Sensing: 1D Array Case



□ Cramer-Rao bound (CRB) of the mean square error (MSE) for the estimation of spatial AoA  $u \triangleq \cos \vartheta$ :

$$\text{CRB}_u(\mathbf{x}) = \frac{\sigma^2 \lambda^2}{8\pi^2 T P N |\beta|^2} \frac{1}{\text{var}(\mathbf{x})}$$

Additional DoF via  
adjusting antenna position  
for minimizing CRB

$\lambda$ : wavelength  
 $T$ : number of snapshots  
 $P/\sigma^2$ : SNR  
 $N$ : number of antennas  
 $\beta$ : complex path coefficient

$\mathbf{x} = [x_1, \dots, x_N]^T$ : antenna position vector (APV)  
 $\text{var}(\mathbf{x}) \triangleq \frac{1}{N} \sum_{n=1}^N x_n^2 - \mu(\mathbf{x})^2$ : variance of  $\mathbf{x}$   
 $\mu(\mathbf{x}) \triangleq \frac{1}{N} \sum_{n=1}^N x_n$ : mean of  $\mathbf{x}$

W. Ma, L. Zhu, and R. Zhang, "Movable antenna enhanced wireless sensing via antenna position optimization," IEEE Transactions on Wireless Communications, vol. 23, no. 11, pp. 16575-16589, Nov. 2024.

# Problem Formulation

□ **Objective:** Minimize  $\text{CRB}_u(\mathbf{x})$  by optimizing APV  $\mathbf{x}$

$$\min_{\mathbf{x}} \text{CRB}_u(\mathbf{x}) \iff \max_{\mathbf{x}} \text{var}(\mathbf{x})$$

$$\max_{\mathbf{x}} \text{var}(\mathbf{x})$$

$$\text{s.t. } x_1 \geq 0, x_N \leq A,$$

$$x_n - x_{n-1} \geq D, \quad n = 2, 3, \dots, N.$$

Variance of APV  $\mathbf{x}$

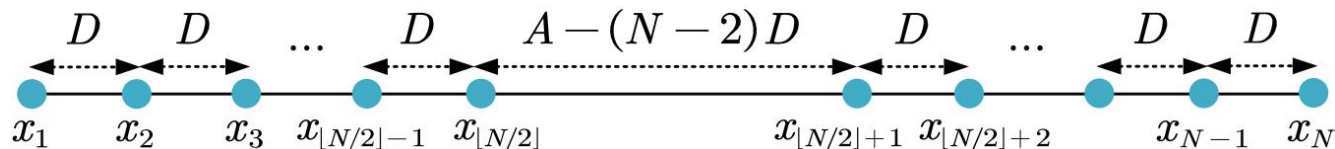
Moving region constraint

Minimum distance constraint

□ **Solution:** The optimal APV for minimizing the CRB can be obtained in closed form:

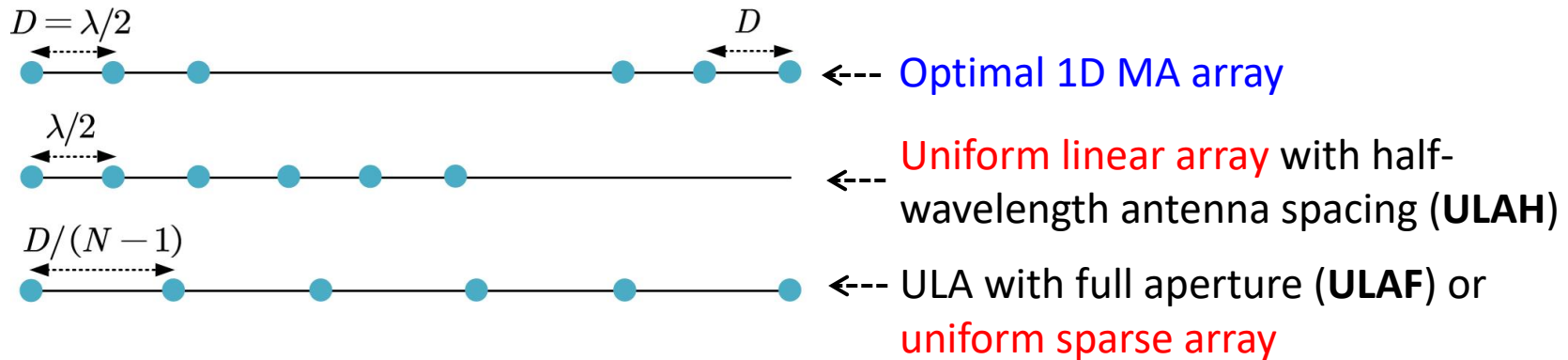
$$x_n^* = \begin{cases} (n-1)D, & n = 1, 2, \dots, \lfloor N/2 \rfloor; \\ A - (N-n)D, & n = \lfloor N/2 \rfloor + 1, \dots, N. \end{cases}$$

□ **Illustration:**

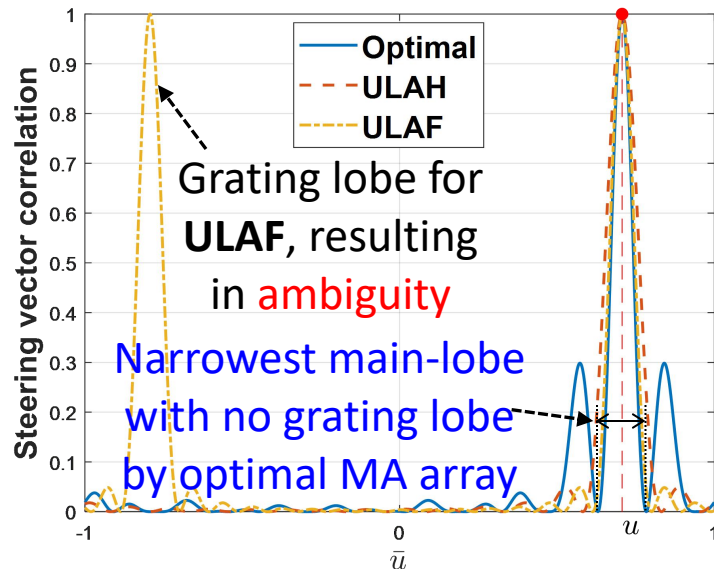


# 1D MA Sensing: Performance Evaluation

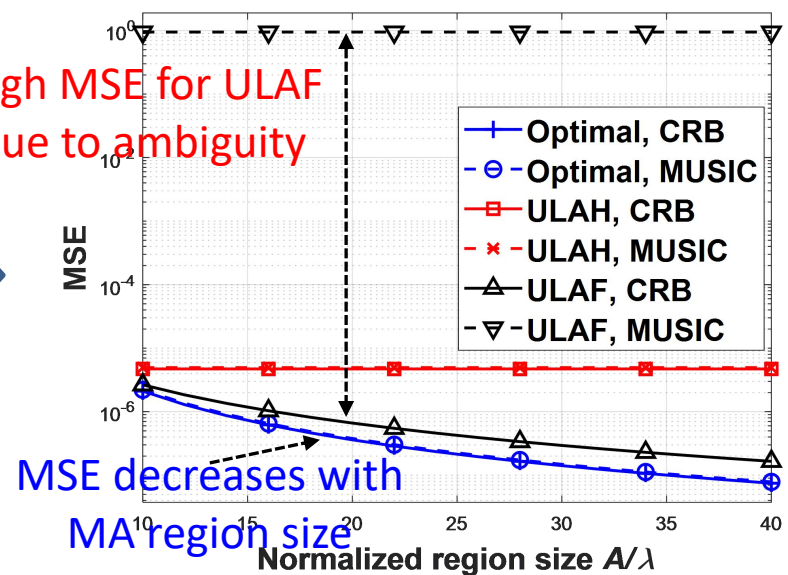
## Array Geometries:



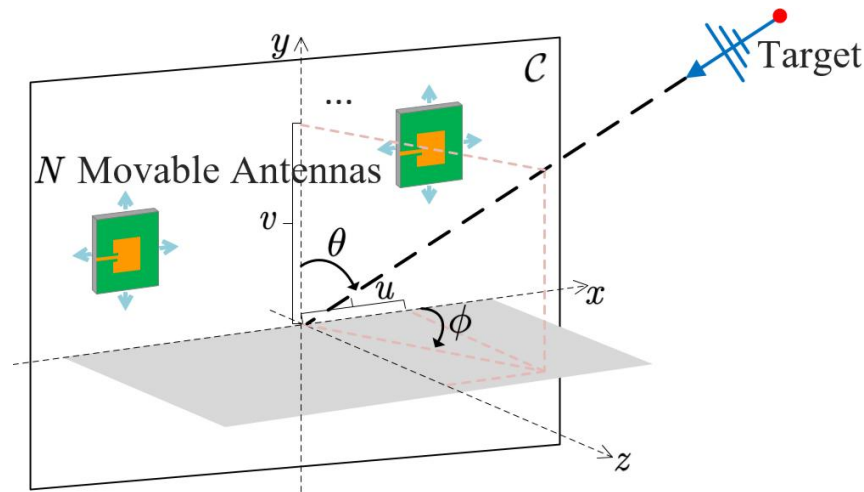
## Numerical Results:



High MSE for ULAF due to ambiguity



# MA-Enhanced Wireless Sensing: 2D Array Case



□ CRB of the estimation MSE of two spatial AoAs  $u \triangleq \sin \theta \cos \phi$ ,  $v \triangleq \cos \theta$ :

$$\text{CRB}_u(\tilde{\mathbf{r}}) = \frac{\sigma^2 \lambda^2}{8\pi^2 T P N |\beta|^2} \frac{1}{\text{var}(\mathbf{x}) - \frac{\text{cov}(\mathbf{x}, \mathbf{y})^2}{\text{var}(\mathbf{y})}}$$

$$\text{CRB}_v(\tilde{\mathbf{r}}) = \frac{\sigma^2 \lambda^2}{8\pi^2 T P N |\beta|^2} \frac{1}{\text{var}(\mathbf{y}) - \frac{\text{cov}(\mathbf{x}, \mathbf{y})^2}{\text{var}(\mathbf{x})}}$$

$\mathbf{x} = [x_1, \dots, x_N]^T$ : x-axis APV

$\mathbf{y} = [y_1, \dots, y_N]^T$ : y-axis APV

$\text{cov}(\mathbf{x}, \mathbf{y}) \triangleq \frac{1}{N} \sum_{n=1}^N x_n y_n - \mu(\mathbf{x}) \mu(\mathbf{y})$ :  
covariance of  $\mathbf{x}$  and  $\mathbf{y}$

Jointly determined by the  
horizontal and vertical  
positions of antennas

# Problem Formulation

□ **Objective:** Min-max  $\text{CRB}_u(\tilde{\mathbf{r}})$  and  $\text{CRB}_v(\tilde{\mathbf{r}})$  by optimizing  $\tilde{\mathbf{r}} = [\mathbf{x}, \mathbf{y}]$

$$\min_{\tilde{\mathbf{r}}} \max [\text{CRB}_u(\tilde{\mathbf{r}}), \text{CRB}_v(\tilde{\mathbf{r}})] \iff \max_{\tilde{\mathbf{r}}} \min \left[ \text{var}(\mathbf{x}) - \frac{\text{cov}(\mathbf{x}, \mathbf{y})^2}{\text{var}(\mathbf{y})}, \text{var}(\mathbf{y}) - \frac{\text{cov}(\mathbf{x}, \mathbf{y})^2}{\text{var}(\mathbf{x})} \right]$$

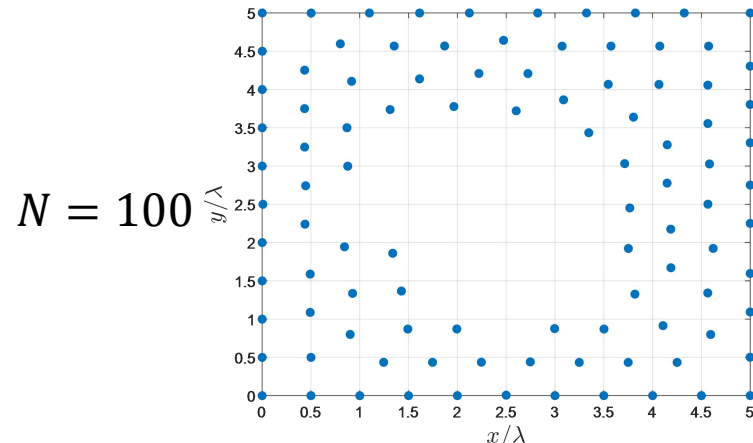
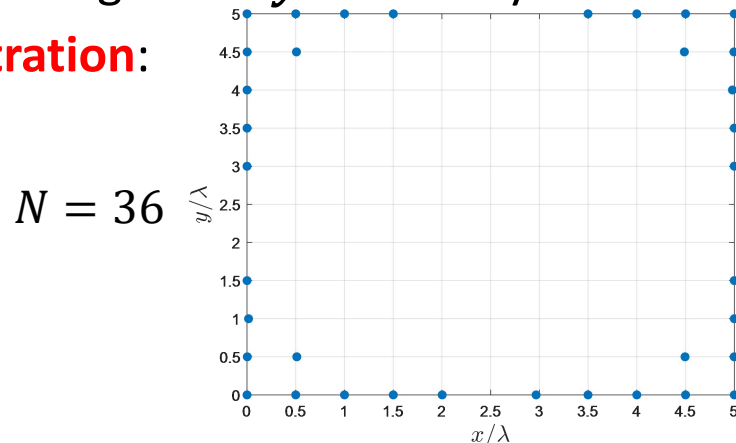
$$\begin{aligned} &\max_{\tilde{\mathbf{r}}, \delta} \delta \\ &\text{s.t.} \quad \text{var}(\mathbf{x}) - \text{cov}(\mathbf{x}, \mathbf{y})^2 / \text{var}(\mathbf{y}) \geq \delta, \\ &\quad \text{var}(\mathbf{y}) - \text{cov}(\mathbf{x}, \mathbf{y})^2 / \text{var}(\mathbf{x}) \geq \delta, \\ &\quad \tilde{\mathbf{r}} \in \mathcal{C}, \\ &\quad \|\mathbf{r}_k - \mathbf{r}_l\|_2 \geq D, \quad 1 \leq k, l \leq N, \quad k \neq l \end{aligned}$$

Moving region constraint

Minimum distance constraint

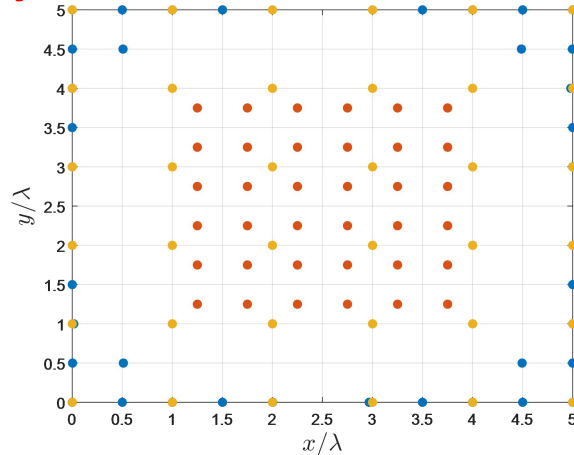
□ **Solution:** Alternating optimization and successive convex approximation for optimizing  $\mathbf{x}$  and  $\mathbf{y}$  iteratively

□ **Illustration:**

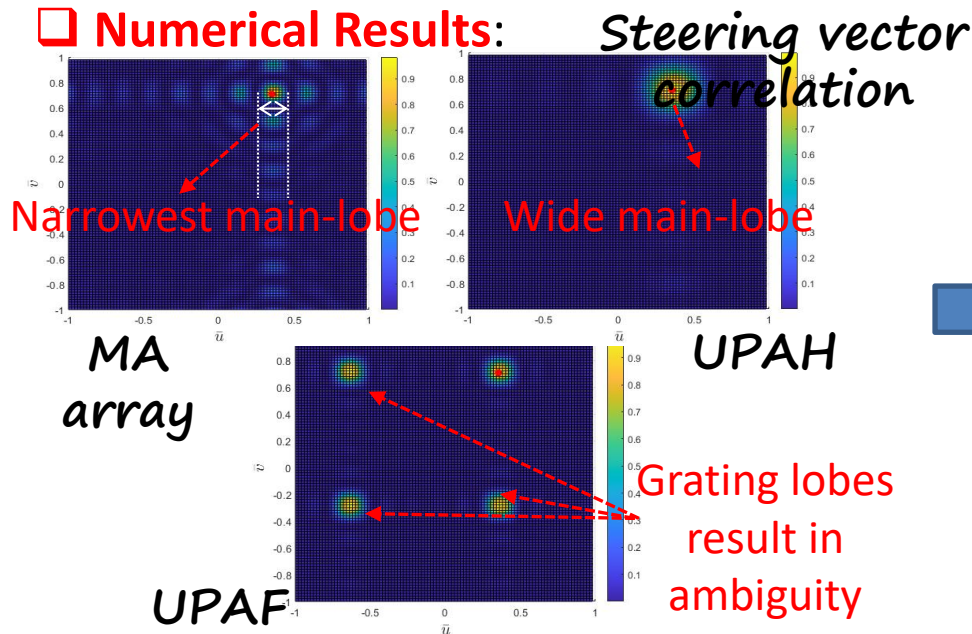


# 2D MA Sensing: Performance Evaluation

## Array Geometries:

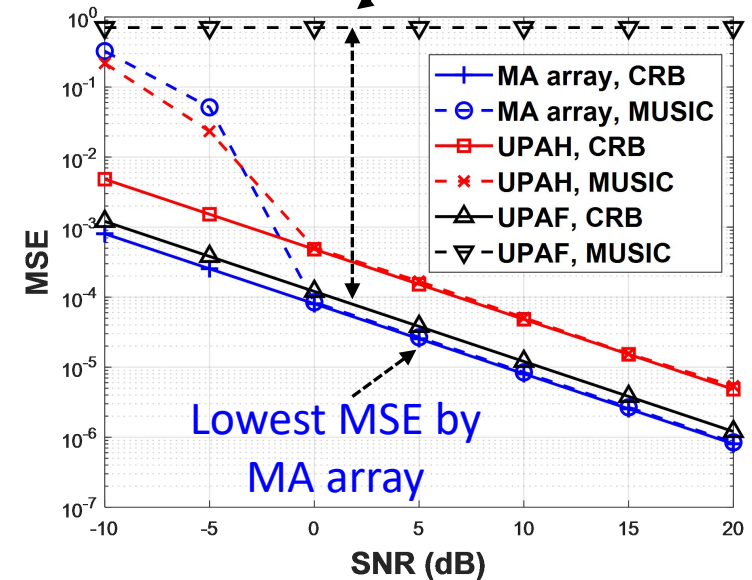


## Numerical Results:



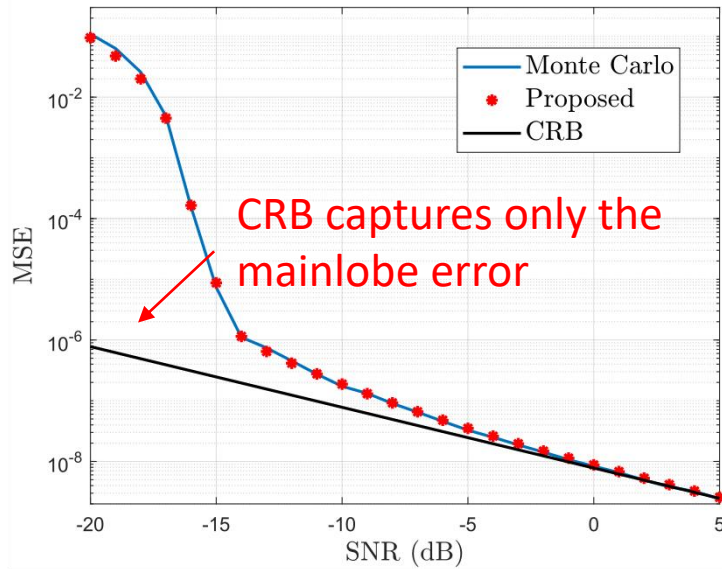
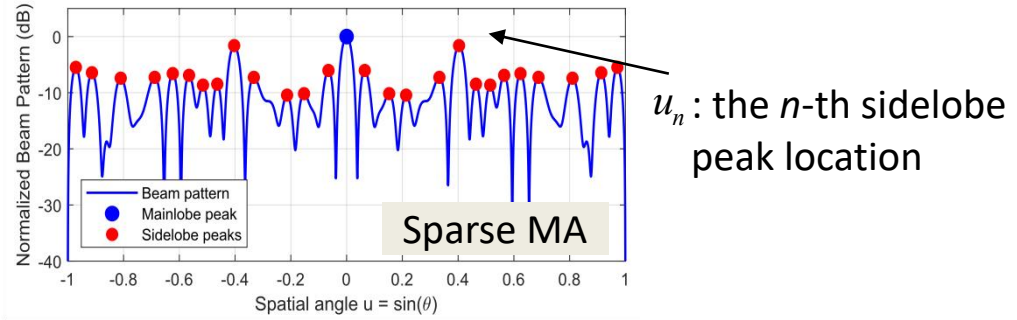
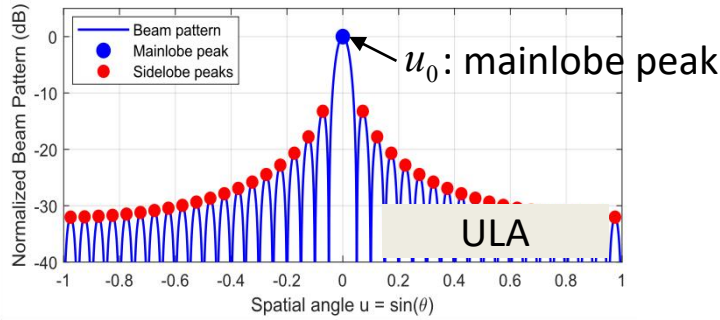
- Optimal 2D MA array
- Uniform planar array (UPA) with half-wavelength antenna spacing (**UPAH**)
- UPA with full aperture or uniform sparsity (**UPAF**)

High MSE for UPAF due to ambiguity



# MA-Enhanced low SNR Wireless Sensing

## □ MSE Approximation:



Mainlobe estimation variance      Sidelobe outlier error

$$\text{MSE}(\mathbf{x}) \approx \left( 1 - \sum_{n=1}^{N_p} P_n \right) \left[ \frac{T\gamma}{J} \Phi \left( \sqrt{\frac{T\gamma}{2}} \right) + J^{-1} \Gamma_{3/2} \left( \frac{T\gamma}{4} \right) \right] + \sum_{n=1}^{N_p} P_n (u_n - u_0)^2$$

$P_n$ : the probability of selecting the  $n$ -th sidelobe peak

$$P_n = \mathcal{Q} \left( \sqrt{\frac{S}{2} (1 - \sqrt{1 - r_n^2})}, \sqrt{\frac{S}{2} (1 + \sqrt{1 - r_n^2})} \right) - e^{-\frac{S}{2}} I_0 \left( \frac{r_n S}{2} \right) \left[ 1 - \frac{1}{2^{2T-1}} \sum_{m=0}^{T-1} \binom{2T-1}{m} \right] \\ + \frac{1}{2^{2T-1}} \sum_{m=1}^{T-1} \left\{ e^{-\frac{S}{2}} I_m \left( \frac{r_n S}{2} \right) \sum_{k=0}^{2T-1-m} \binom{2T-1}{k} \times \left[ \left( \frac{1 + \sqrt{1 - r_n^2}}{r_n} \right)^m - \left( \frac{1 - \sqrt{1 - r_n^2}}{r_n} \right)^m \right] \right\},$$

$J$ : Fisher information

$$J \triangleq \frac{8\pi^2 T\gamma}{N\lambda^2} \mathbf{x}^T \left( \mathbf{I}_N - \frac{1}{N} \mathbf{1}\mathbf{1}^T \right) \mathbf{x}$$

Parameters:

$$\gamma \triangleq \frac{N^2 \text{SNR}^2}{1 + N \text{SNR}}, \Phi(z) \triangleq \int_z^\infty \frac{1}{\sqrt{2\pi}} e^{-v^2/2} dv$$

W. Chen, L. Zhu, W. Ma, Z. Chen, and R. Zhang, "MSE Minimization for Movable Antenna Enhanced Wireless Sensing via Array Geometry Optimization", arXiv preprint arXiv:2610.14882, 2026.

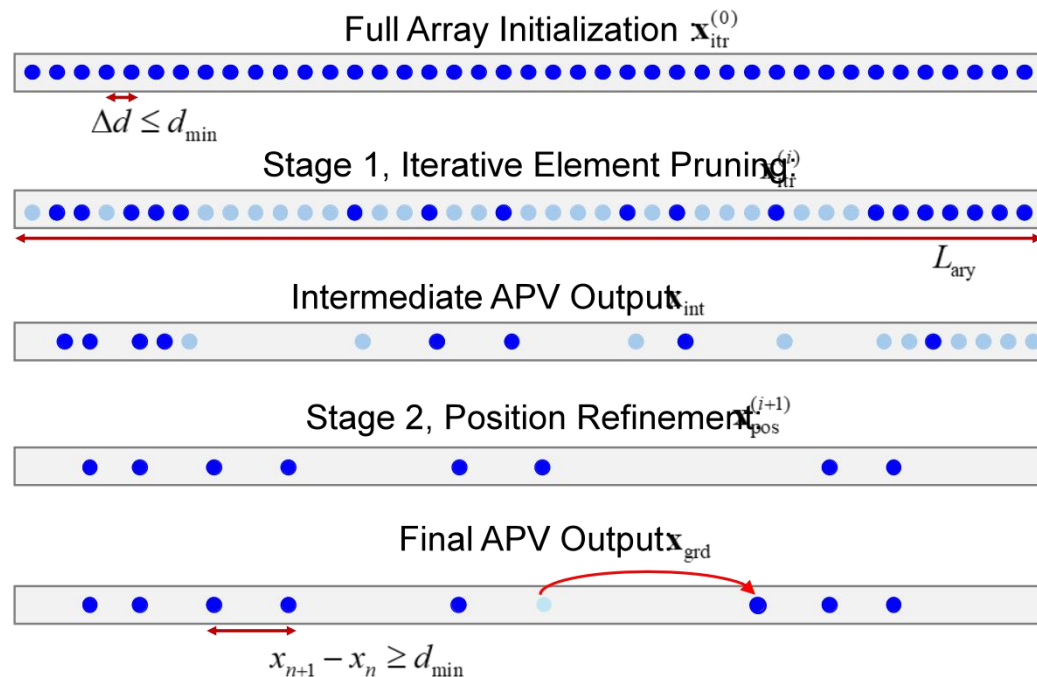
# MA geometry——Movable Free Array (MFA)

□ **Objective:** Minimize  $\text{MSE}(\mathbf{x})$  by optimizing APV  $\mathbf{x}$

$$\begin{aligned}
 & \text{(Q)} \quad \min_{\mathbf{x}} \quad \text{MSE}(\mathbf{x}) \\
 & \text{s.t.} \quad 0 = x_1 < x_2 < \dots < x_N \leq L_{\text{ary}}, \quad \text{(Moving region constraint)} \\
 & \quad \quad x_{n+1} - x_n \geq \frac{\lambda}{2}, n = 1, \dots, N-1. \quad \text{(Minimum distance constraint)}
 \end{aligned}$$

□ **Case 1: full-independent motors——MFA**

- Two-stage greedy search



## Stage 1: Iterative Element Pruning

Start from a dense grid; remove the element causing the smallest MSE increase until  $N$  remain.

## Stage 2: Position Refinement

Iteratively move each element in turn to its MSE-minimizing feasible position. Repeat until convergence

# MA geometry——Movable Twin Array (MTA)

## Case 2: Single motor——MTA:

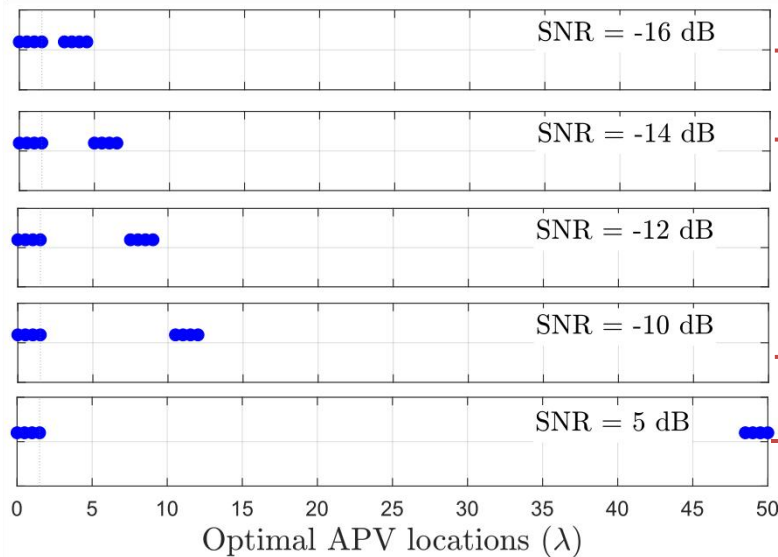
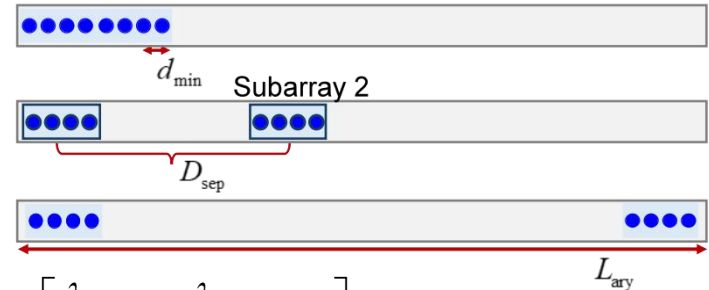
Splits the MAs into two half-wavelength ULA subarrays and adjusts their separation

where

$$\mathbf{x}_{\text{MT},1} = \frac{\lambda}{2} \cdot [0, 1, 2, \dots, N_1 - 1]^T,$$

$$\mathbf{x}_{\text{MT},2} = D_{\text{sep}} + \frac{\lambda}{2} \cdot [0, 1, 2, \dots, N_2 - 1]^T,$$

the separation  $D_{\text{sep}}^* = \arg \min_{D_{\text{sep}}} \text{MSE}_{\text{MT}}(\mathbf{x}_{\text{MT}}(D_{\text{sep}}))$ ,  $D_{\text{sep}} \in \left[ \frac{\lambda}{2}, L_{\text{ary}} - \frac{\lambda}{2}(N_2 - 1) \right]$ .



1. Merged to suppress sidelobes

2. Move apart as SNR rises

3. Fully separated to maximize the aperture

# MA geometry——Movable Nested Array (MNA)

## Case 3: limited number of motors——MNA

Two subarrays  $\mathbf{x}_{MN} = [\mathbf{x}_{MN,1}^T, \mathbf{x}_{MN,2}^T]^T$ ,

1. Fixed dense inner subarray ( $N_1$  elements)

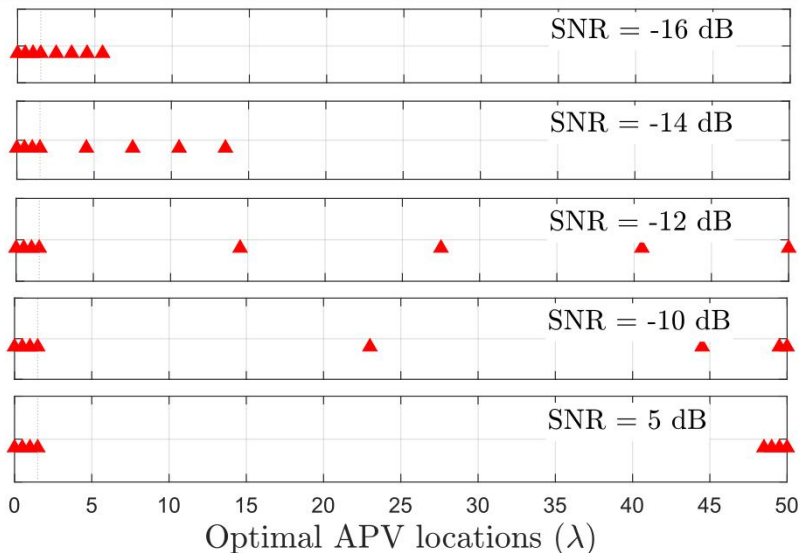
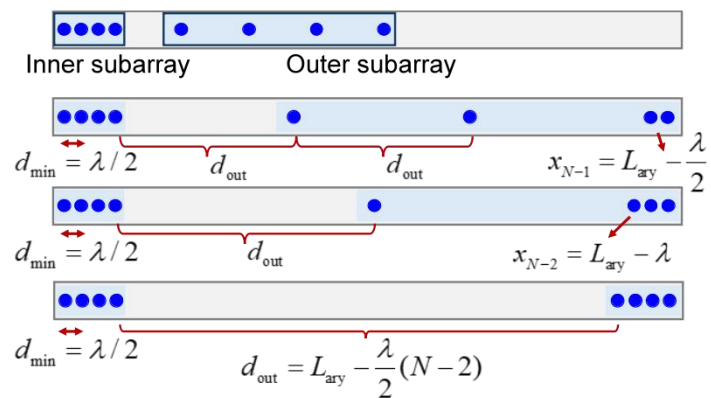
$$\mathbf{x}_{MN,1} = \frac{\lambda}{2} \cdot [0, 1, 2, \dots, N_1 - 1]^T, n = 1, \dots, N_1$$

2. Movable sparse outer subarray ( $N_2$  elements)

$$\mathbf{x}_{MN,2}(n) = \min \left[ \underbrace{\frac{\lambda}{2}(N_1 - 1) + nd_{out}}_{\text{nominal position}}, \underbrace{L_{ary} - (N_2 - n)\frac{\lambda}{2}}_{\text{edge limit}} \right], n = 1, \dots, N_2$$

the outer spacing

$$d_{out} = \arg \min_{d_{out}} \text{MSE}(\mathbf{x}_{MN}(d_{out})), \quad d_{out} \in \left[ \frac{\lambda}{2}, L_{ary} - \frac{\lambda}{2}(N - 2) \right].$$



1. Low SNR, outer spacing stays small, ULA-like

2. Expand to widen the aperture

3. Progressively pushed into the edge cluster

4. Clustered at the edge, forming split ULA (SULA)

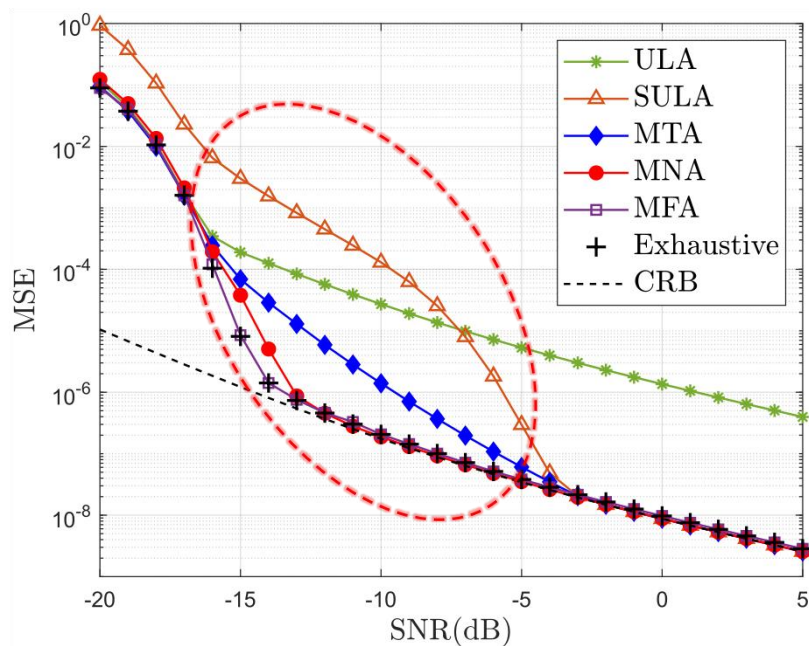
# Performance Evaluation

## Complexity comparison

| Array Geometry    | Computational Complexity                                                            | Motors |
|-------------------|-------------------------------------------------------------------------------------|--------|
| Exhaustive Search | $\mathcal{O}\left[e^{N_{\text{all}} H\left(\frac{N}{N_{\text{all}}}\right)}\right]$ | $N$    |
| MFA               | $\mathcal{O}(N_{\text{all}}^2)$                                                     | $N$    |
| MNA               | $\mathcal{O}\left(\frac{L_{\text{ary}} - \frac{\lambda}{2} N_1}{\Delta d}\right)$   | $N/2$  |
| MTA               | $\mathcal{O}\left(\frac{L_{\text{ary}} - \frac{\lambda}{2} N_2}{\Delta d}\right)$   | 1      |

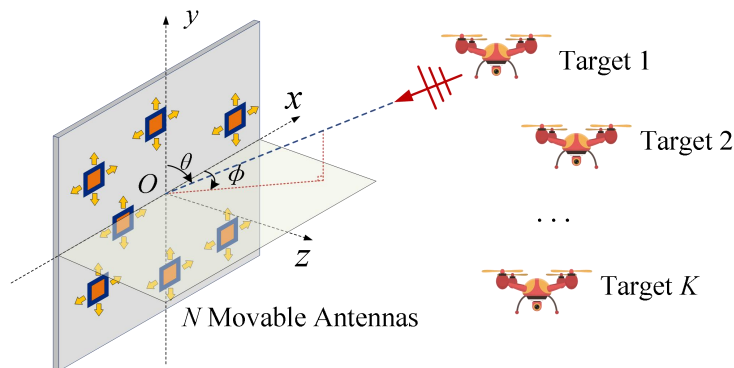
- MFA reduces exhaustive search from **exponential to quadratic** complexity.
- MNA and MTA further trade motor freedom for **linear complexity**.

## Numerical results



1. MFA approaches the exhaustive-search with far lower computational complexity.
2. MNA stays near-optimal with half the motors.
3. MTA offers the lowest hardware cost but loses some mid-SNR accuracy.

# MA-Enhanced Multi-Target Sensing



- Cramer-Rao bound (CRB) of the mean square error (MSE) for the estimation of two spatial AoAs of multiple targets,  $\mathbf{r}_k = [u_k, v_k]^T$ ,  $u_k \triangleq \cos \varphi_k \sin \theta_k$ ,  $v_k \triangleq \cos \theta_k$ :

$$\text{CRB}(\tilde{\mathbf{q}}) = \frac{\sigma^2}{2} \left( \Re \left\{ (\mathbf{1}_2 \otimes \mathbf{R}_S^T) \odot \dot{\mathbf{A}}^H \boldsymbol{\Pi}_A^\perp \dot{\mathbf{A}} \right\} \right)^{-1}$$

Additional DoF via  
adjusting antenna position  
for minimizing CRB

$\mathbf{1}_2$ : matrix with all elements being 1  
 $\mathbf{R}_S$ : covariance matrix of the received source signals

$\dot{\mathbf{A}} = [\dot{\mathbf{A}}_u, \dot{\mathbf{A}}_v]$ : each column vector is the derivative of the steering vector of each target w.r.t. its angular position

$\boldsymbol{\Pi}_A^\perp = \mathbf{I}_N - \mathbf{A}(\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H$ : orthogonal projection matrix of the column space of  $\mathbf{A}$

# Problem Formulation

❑ **Objective:** Min the expectation of the trace of  $\text{CRB}(\tilde{\mathbf{q}})$  by optimizing APV  $\tilde{\mathbf{q}} = [\tilde{\mathbf{x}}, \tilde{\mathbf{y}}]$

$$\begin{aligned} \min_{\tilde{\mathbf{q}}} \mathbb{E} \{ \text{tr}(\text{CRB}(\tilde{\mathbf{q}})) \} \\ \text{s.t. } \|\mathbf{q}_{n'} - \mathbf{q}_n\|_2 \geq d_{\min}, 1 \leq n \neq n' \leq N, \\ \mathbf{q}_n \in \mathcal{C}, 1 \leq n \leq N, \end{aligned}$$

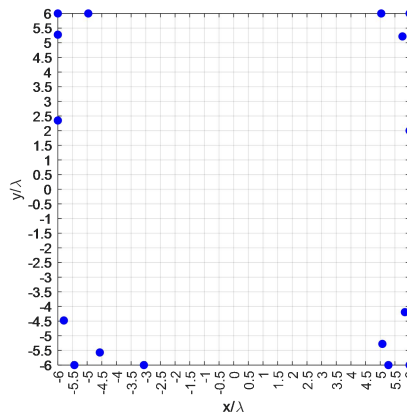
Minimum distance constraint

Moving region constraint

❑ **Solution:** Monte Carlo method for approximating the objective function, alternating optimization and swarm-based gradient descent for optimizing each antenna's positions iteratively

❑ **Illustration:**

$N = 16$



# Performance Lower-bound Analysis

## Lower-bound of the approximated objective function:

$$\tilde{\psi}(\tilde{\mathbf{q}}) \stackrel{(a)}{\geq} \frac{K\sigma^2\lambda^2}{8NTP_s\pi^2} \left( \frac{1}{\text{var}(\tilde{\mathbf{x}}) - \frac{\text{cov}(\tilde{\mathbf{x}}, \tilde{\mathbf{y}})^2}{\text{var}(\tilde{\mathbf{y}})}} + \frac{1}{\text{var}(\tilde{\mathbf{y}}) - \frac{\text{cov}(\tilde{\mathbf{x}}, \tilde{\mathbf{y}})^2}{\text{var}(\tilde{\mathbf{x}})}} \right) \stackrel{(b)}{\geq} \frac{K\sigma^2\lambda^2}{NTP_sA^2\pi^2}$$

$\lambda$ : wavelength  
 $T$ : number of snapshots  
 $P_s/\sigma^2$ : SNR  
 $N$ : number of antennas  
 $K$ : number of targets  
 $A$ : square region size

## To approach the lower-bound via optimizing APV:

- Decrease the *correlation* of sensitivity

$$\rho_{k,k'}(\iota, \iota') = \frac{|\dot{\mathbf{a}}_\iota(\tilde{\mathbf{q}}, \mathbf{r}_k)^H \mathbf{\Pi}_A^\perp \dot{\mathbf{a}}_{\iota'}(\tilde{\mathbf{q}}, \mathbf{r}_{k'})|^2}{\|\mathbf{\Pi}_A^\perp \dot{\mathbf{a}}_\iota(\tilde{\mathbf{q}}, \mathbf{r}_k)\|_2^2 \|\mathbf{\Pi}_A^\perp \dot{\mathbf{a}}_{\iota'}(\tilde{\mathbf{q}}, \mathbf{r}_{k'})\|_2^2}, 1 \leq k \neq k' \leq K, \iota, \iota' \in \{\mathbf{u}, \mathbf{v}\}$$

*sensitivity vector*: the projection of the derivative of the steering vector of each target w.r.t. its angular position into the noise subspace

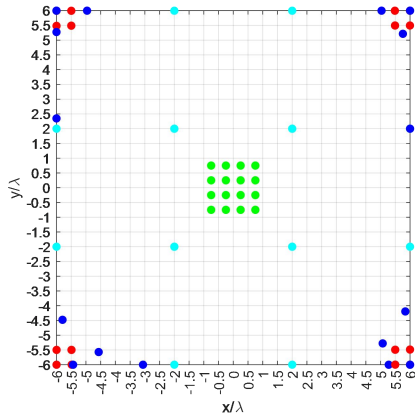
- Increase the *effective power* of sensitivity vectors

$$\omega_{\mathbf{u},k} = \|\mathbf{\Pi}_A^\perp \dot{\mathbf{a}}_{\mathbf{u}}(\tilde{\mathbf{q}}, \mathbf{r}_k)\|_2^2 - \frac{\Re\left\{\dot{\mathbf{a}}_{\mathbf{u}}^H(\tilde{\mathbf{q}}, \mathbf{r}_k) \mathbf{\Pi}_A^\perp \dot{\mathbf{a}}_{\mathbf{v}}(\tilde{\mathbf{q}}, \mathbf{r}_k)\right\}^2}{\|\mathbf{\Pi}_A^\perp \dot{\mathbf{a}}_{\mathbf{v}}(\tilde{\mathbf{q}}, \mathbf{r}_k)\|_2^2}$$

*interference* between the estimation of each target's 2D spatial AoAs

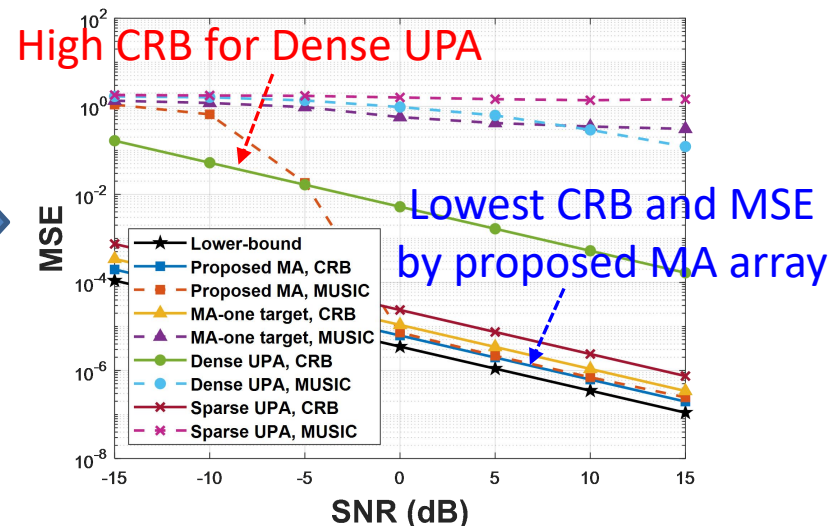
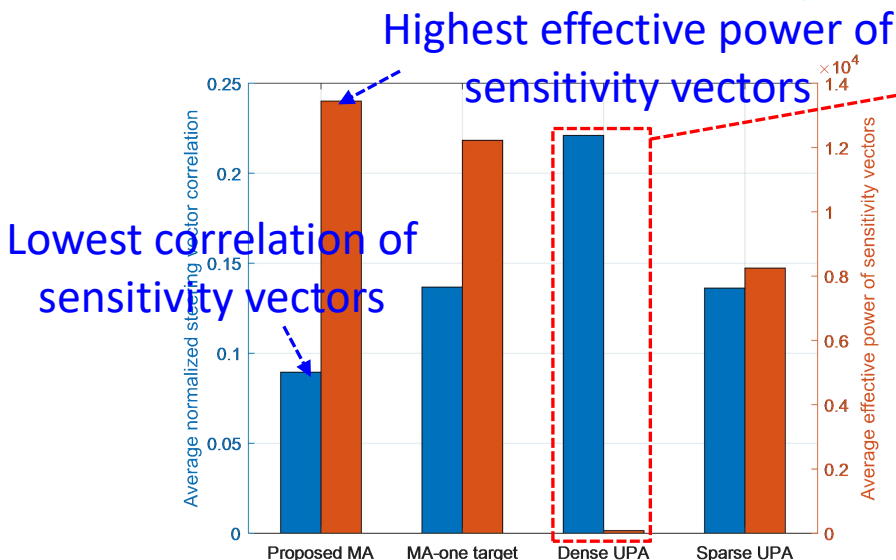
# MA Multi-Target Sensing: Performance Evaluation

## Array Geometries:

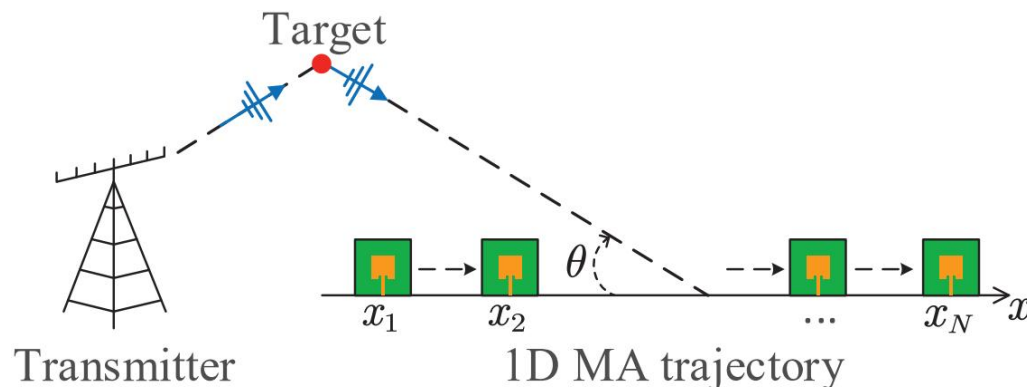


- Lower-bound
- **Proposed MA array**
- Single-target oriented MA array (**MA-one target**)
- Uniform planar array (UPA) with half-wavelength antenna spacing (**Dense UPA**)
- UPA with full aperture or uniform sparsity (**Sparse UPA**)

## Numerical Results: Correlation and effective power of sensitivity vectors



# MA-Enhanced Wireless Sensing: 1D Trajectory Case



- Antenna position  $x_n$  ( $n = 2, \dots, N$ ) w.r.t. its initial position  $x_1$  and the velocity  $\{v_n\}_{n=1}^{N-1}$ :

$$x_n = x_1 + T_s \sum_{m=1}^{n-1} v_m$$

- CRB of the MSE for the estimation of spatial AoA  $u \triangleq \cos \theta$ :

$$\text{CRB}_u(\mathbf{x}) = \frac{\sigma^2 \lambda^2}{8\pi^2 P N |\beta|^2} \frac{1}{\text{var}(\mathbf{x})}$$

Additional DoF via adjusting antenna trajectory for minimizing CRB

$\lambda$ : wavelength  
 $N$ : number of snapshots  
 $P/\sigma^2$ : SNR  
 $\beta$ : complex path coefficient

$\mathbf{x} = [x_1, \dots, x_N]^T$ : antenna position vector (APV)  
 $\text{var}(\mathbf{x}) \triangleq \frac{1}{N} \sum_{n=1}^N x_n^2 - \mu(\mathbf{x})^2$ : variance of  $\mathbf{x}$   
 $\mu(\mathbf{x}) \triangleq \frac{1}{N} \sum_{n=1}^N x_n$ : mean of  $\mathbf{x}$

W. Ma, L. Zhu, and R. Zhang, "Movable-antenna trajectory optimization for wireless sensing: CRB scaling laws over time and space," IEEE Transactions on Wireless Communications, vol. 25, pp. 19709-19724, 2026.

# Problem Formulation

❑ **Objective:** Minimize  $\text{CRB}_u(\mathbf{x})$  by optimizing APV  $\mathbf{x}$  and velocity vector  $\mathbf{v}$

$$\min_{\mathbf{x}, \mathbf{v}} \text{CRB}_u(\mathbf{x}) \iff \max_{\mathbf{x}, \mathbf{v}} \text{var}(\mathbf{x})$$

$$\begin{aligned} & \max_{\mathbf{x}, \mathbf{v}} \quad \text{var}(\mathbf{x}) \\ & \text{s.t.} \quad -v^m \leq v_n \leq v^m, \quad n = 1, \dots, N-1, \\ & \quad \quad 0 \leq x_n \leq A, \quad n = 1, \dots, N, \\ & \quad \quad x_n = x_1 + T_s \sum_{m=1}^{n-1} v_m, \quad n = 2, \dots, N. \end{aligned}$$

Annotations:

- Variance of APV  $\mathbf{x}$
- Maximum speed constraint
- Moving region constraint
- Trajectory constraint

❑ **Solution:** The optimal  $\mathbf{x}$  and  $\mathbf{v}$  can be obtained in closed form ( $\Delta \triangleq v^m T_s$ ):

**Time-constrained**

(TC) regime:

$$A \geq (N-1)\Delta$$

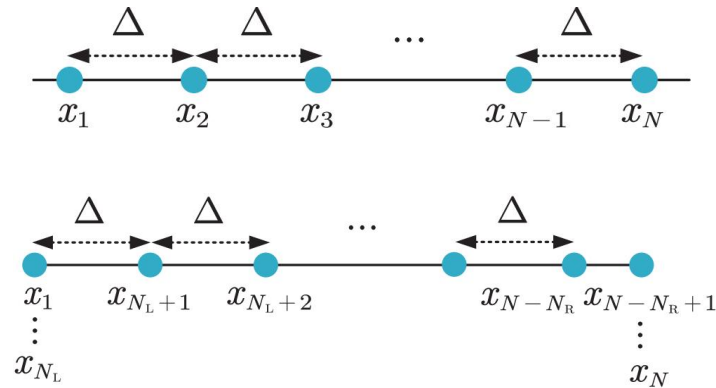
**Space-constrained**

(SC) regime:

$$A < (N-1)\Delta$$

$$v_n^{\text{TC}} = v^m, \quad n = 1, \dots, N-1.$$

$$v_n^{\text{SC}} = \begin{cases} 0, & n = 1, \dots, N_L - 1, \\ v^m, & n = N_L, \dots, N - N_R - 1, \\ \frac{A - N_M \Delta}{T_s}, & n = N - N_R, \\ 0, & n = N - N_R + 1, \dots, N - 1 \end{cases}$$



## Comparison with FPA Array

- ❑ Consider an FPA receiver equipped with an  $M$ -antenna ULA with  $\lambda/2$  spacing. The FPA receives  $N$  reflected signals from the target to estimate the spatial AoA  $u$ , with CRB:

$$\overline{\text{CRB}}_u(\mathbf{x}_{\text{FPA}}) = \frac{6\sigma^2}{\pi^2 P |\beta|^2} \frac{1}{NM^3}$$

$\mathcal{O}(N^{-1})$ : sensing time  
 $\mathcal{O}(M^{-2})$ : array aperture  
 $\mathcal{O}(M^{-1})$ : array gain

- ❑ Consider the TC regime ( $A \geq (N - 1)\Delta$ ):

$$\text{CRB}_u(\mathbf{x}^{\text{TC}}) = \frac{3\sigma^2\lambda^2}{2\pi^2 P |\beta|^2 \Delta^2} \frac{1}{N^3}$$

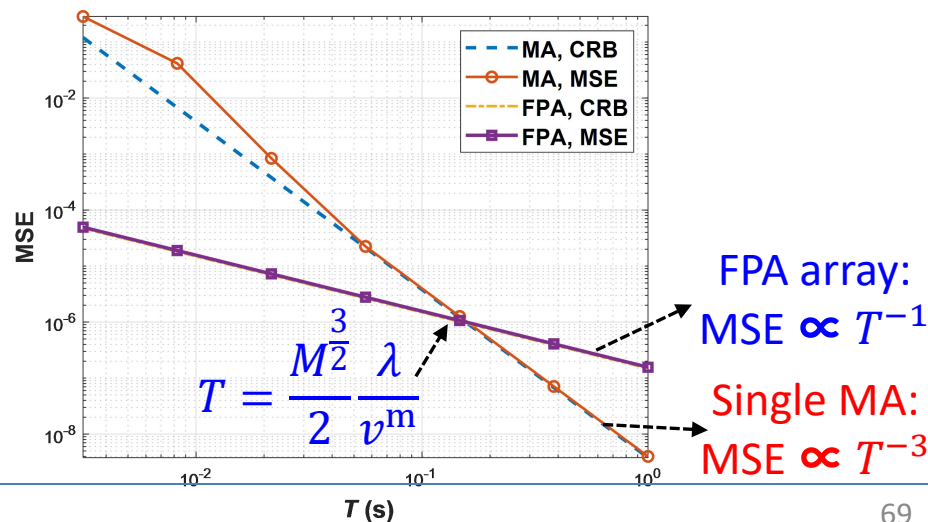
$\mathcal{O}(N^{-1})$ : sensing time  
 $\mathcal{O}(N^{-2})$ : virtual aperture via antenna movement

- ❑ For the MA system to outperform the conventional FPA system, i.e.,

$$\text{CRB}_u(\mathbf{x}^{\text{TC}}) < \overline{\text{CRB}}_u(\mathbf{x}_{\text{FPA}})$$

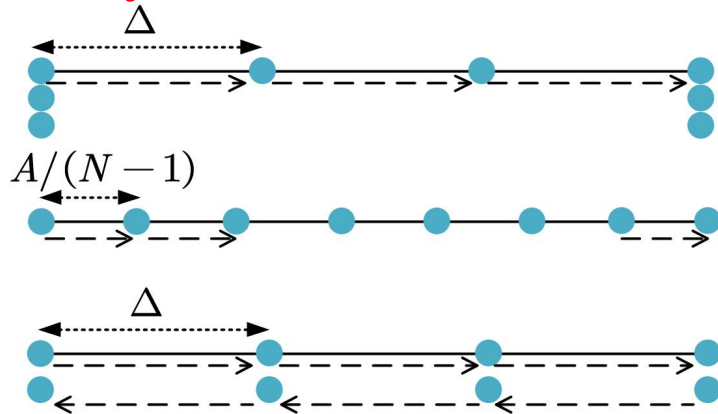


$$T > \frac{M^{\frac{3}{2}}}{2} \frac{\lambda}{v^m}$$



# 1D MA Sensing: Performance Evaluation

## Trajectories:



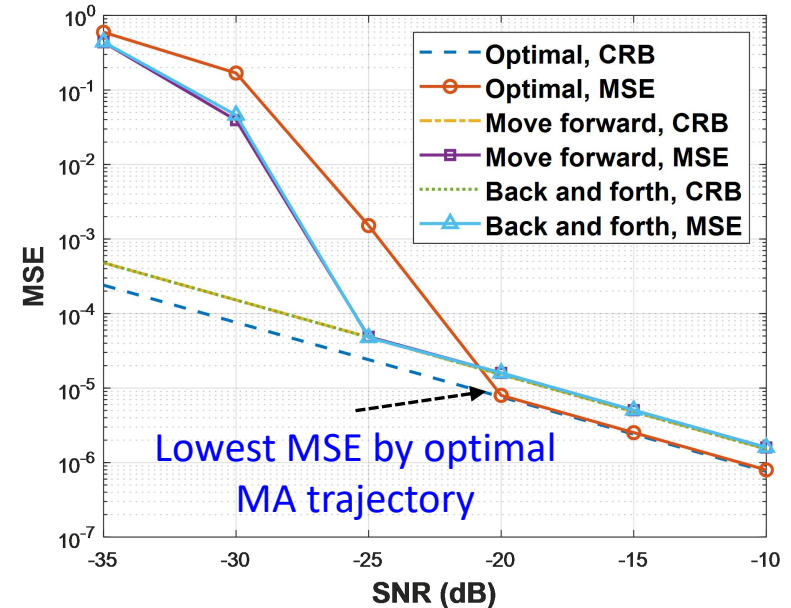
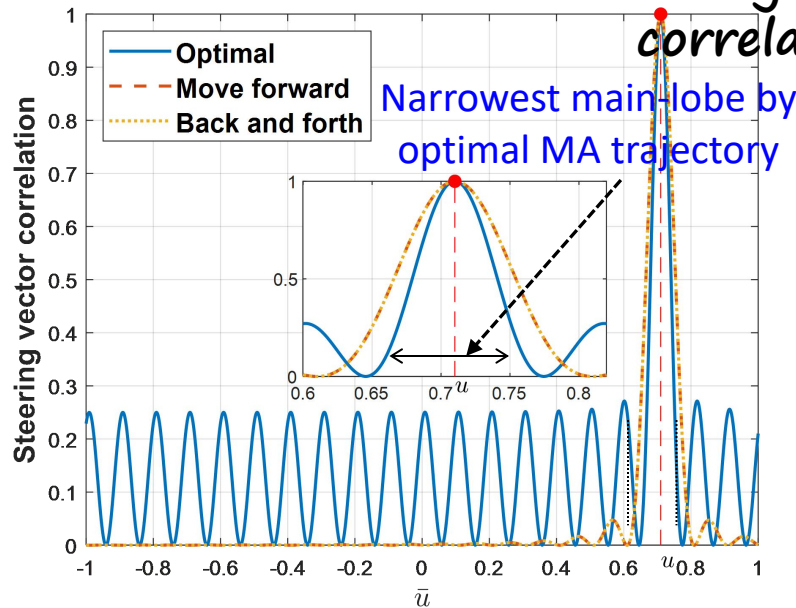
←-- Optimal 1D MA trajectory

←-- Move forward: move with constant speed  $A/(N-1)T_s$

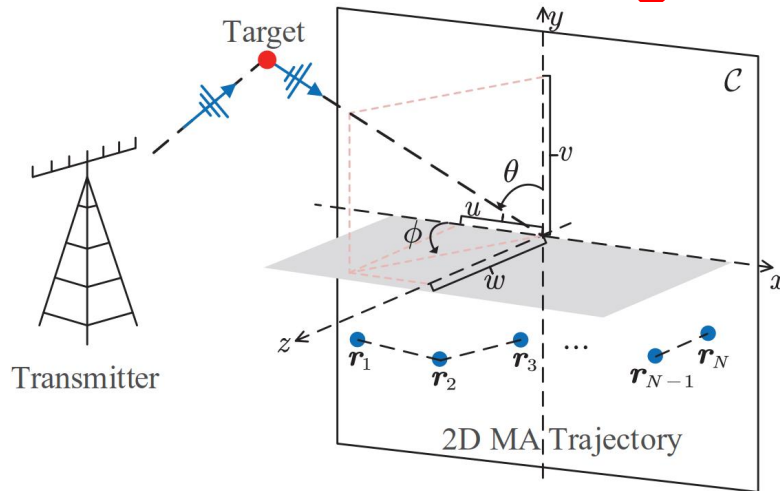
←-- Back and forth: move back and forth with constant speed  $v^m$

## Numerical Results:

Steering vector correlation



# MA-Enhanced Wireless Sensing: 2D Trajectory Case



- Antenna position  $\mathbf{r}_n$  ( $n = 2, \dots, N$ ) w.r.t. its initial position  $\mathbf{r}_1$  and the velocity  $\{\mathbf{v}_n\}_{n=1}^{N-1}$ :

$$\mathbf{r}_n = \mathbf{r}_1 + T_s \sum_{m=1}^{n-1} \mathbf{v}_m$$

- CRB of the estimation MSE of two spatial AoAs  $u \triangleq \sin \theta \cos \phi$ ,  $v \triangleq \cos \theta$ :

$$\text{CRB}_u(\mathbf{R}) = \frac{\sigma^2 \lambda^2}{8\pi^2 P |\beta|^2 N} \frac{1}{\text{var}(\mathbf{x}) - \frac{\text{cov}(\mathbf{x}, \mathbf{y})^2}{\text{var}(\mathbf{y})}}$$

$$\text{CRB}_v(\mathbf{R}) = \frac{\sigma^2 \lambda^2}{8\pi^2 P |\beta|^2 N} \frac{1}{\text{var}(\mathbf{y}) - \frac{\text{cov}(\mathbf{x}, \mathbf{y})^2}{\text{var}(\mathbf{x})}}$$

$\mathbf{x} = [x_1, \dots, x_N]^T$ : x-axis APV

$\mathbf{y} = [y_1, \dots, y_N]^T$ : y-axis APV

$\text{cov}(\mathbf{x}, \mathbf{y}) \triangleq \frac{1}{N} \sum_{n=1}^N x_n y_n - \mu(\mathbf{x}) \mu(\mathbf{y})$ :

covariance of  $\mathbf{x}$  and  $\mathbf{y}$

# Problem Formulation

❑ **Objective:** Min-max  $\text{CRB}_u(\mathbf{R})$  and  $\text{CRB}_v(\mathbf{R})$  by optimizing  $\mathbf{R} = [\mathbf{x}, \mathbf{y}]$  and velocity matrix  $\mathbf{V}$

$$\min_{\mathbf{R}, \mathbf{V}} \max [\text{CRB}_u(\mathbf{R}), \text{CRB}_v(\mathbf{R})] \iff \max_{\mathbf{R}, \mathbf{V}} \min \left[ \text{var}(\mathbf{x}) - \frac{\text{cov}(\mathbf{x}, \mathbf{y})^2}{\text{var}(\mathbf{y})}, \text{var}(\mathbf{y}) - \frac{\text{cov}(\mathbf{x}, \mathbf{y})^2}{\text{var}(\mathbf{x})} \right]$$

$$\max_{\mathbf{R}, \mathbf{V}, \delta}$$

$$\delta$$

$$\text{s.t.} \quad \text{var}(\mathbf{x}) - \frac{\text{cov}(\mathbf{x}, \mathbf{y})^2}{\text{var}(\mathbf{y})} \geq \delta,$$

$$\text{var}(\mathbf{y}) - \frac{\text{cov}(\mathbf{x}, \mathbf{y})^2}{\text{var}(\mathbf{x})} \geq \delta,$$

$$\|\mathbf{v}_n\|_2 \leq v^m, \quad n = 1, \dots, N-1,$$

$$\mathbf{r}_n \in \mathcal{C}, \quad n = 1, \dots, N,$$

$$\mathbf{r}_n = \mathbf{r}_1 + T_s \sum_{m=1}^{n-1} \mathbf{v}_m, \quad n = 2, \dots, N.$$

Maximum speed constraint

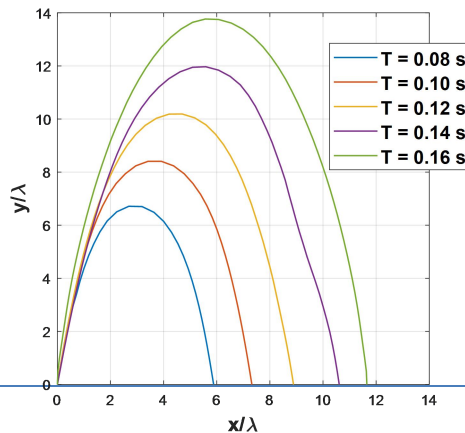
Moving region constraint

Trajectory constraint

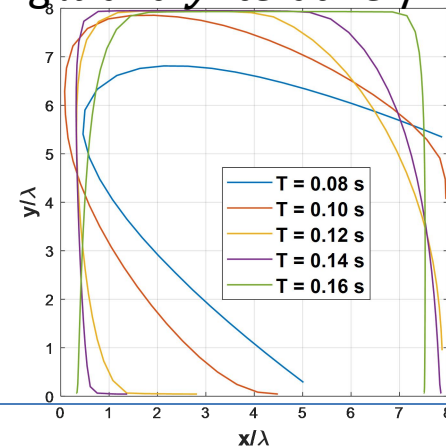
❑ **Solution:** Alternating optimization and SCA for optimizing  $\mathbf{x}$  and  $\mathbf{y}$  iteratively

❑ **Illustration:**

Without region  
size constraint



With region  
size constraint



## Comparison with FPA Array

- ❑ Consider an FPA receiver equipped with an  $\sqrt{M} \times \sqrt{M}$ -antenna UPA with  $\lambda/2$  spacing. The FPA receives  $N$  reflected signals to estimate the spatial AoAs  $u$  and  $v$ , with CRB:

$$\overline{\text{CRB}}_u(\mathbf{R}_{\text{FPA}}) = \overline{\text{CRB}}_v(\mathbf{R}_{\text{FPA}}) = \frac{6\sigma^2}{\pi^2 P |\beta|^2} \frac{1}{NM^2}$$

$\mathcal{O}(N^{-1})$ : sensing time  
 $\mathcal{O}(M^{-1})$ : array aperture  
 $\mathcal{O}(M^{-1})$ : array gain

- ❑ Consider the circular trajectory (MA moves at speed  $v^m$  to form a circle)

$$\text{CRB}_u(\mathbf{R}) = \frac{\sigma^2 \lambda^2}{P |\beta|^2 \Delta^2} \frac{1}{N^3}$$

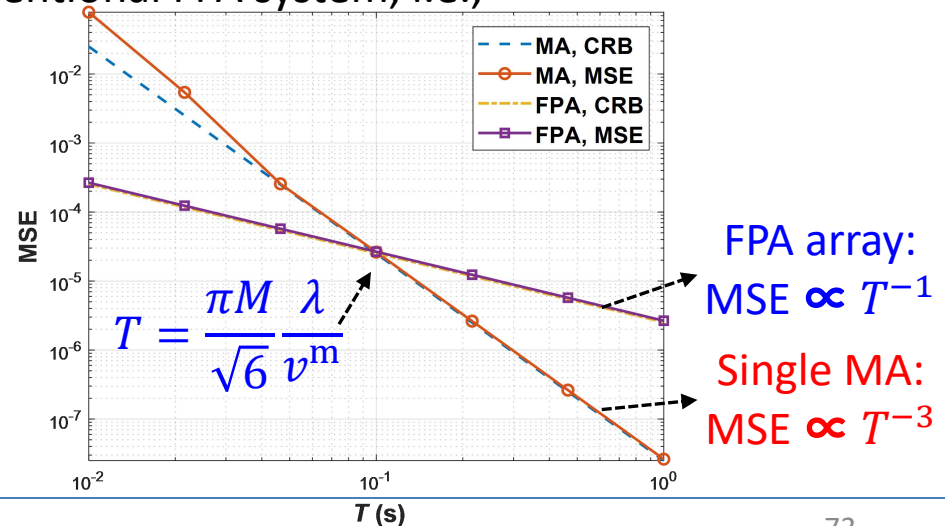
$\mathcal{O}(N^{-1})$ : sensing time  
 $\mathcal{O}(N^{-2})$ : virtual aperture via antenna movement

- ❑ For the MA system to outperform the conventional FPA system, i.e.,

$$\text{CRB}_v(\mathbf{R}) < \overline{\text{CRB}}_v(\mathbf{R}_{\text{FPA}})$$

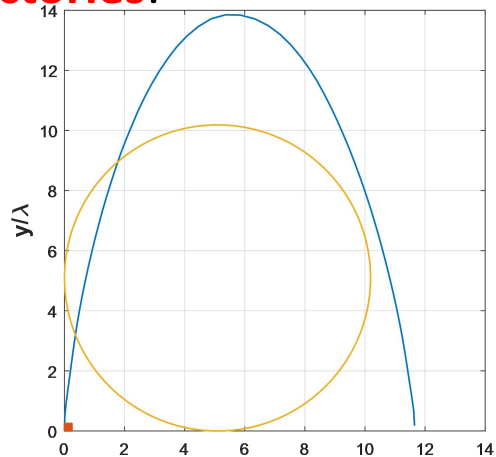


$$T > \frac{\pi M}{\sqrt{6}} \frac{\lambda}{v^m}$$



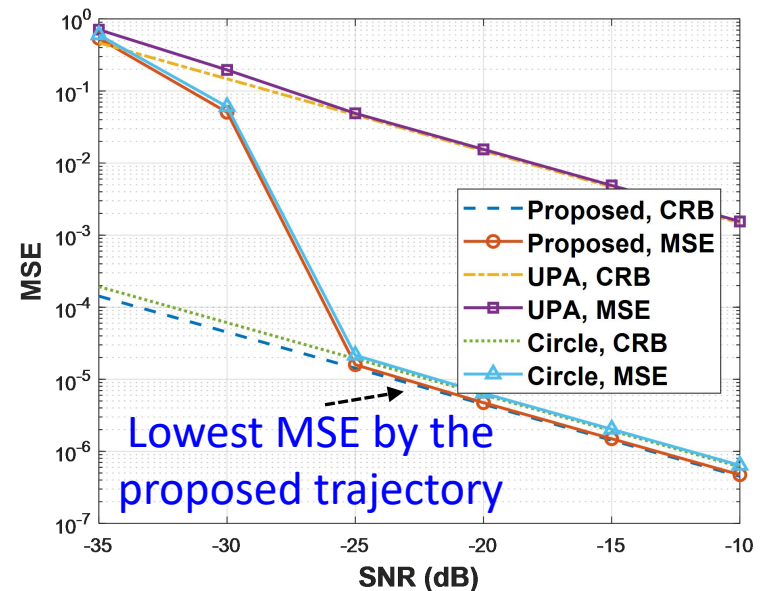
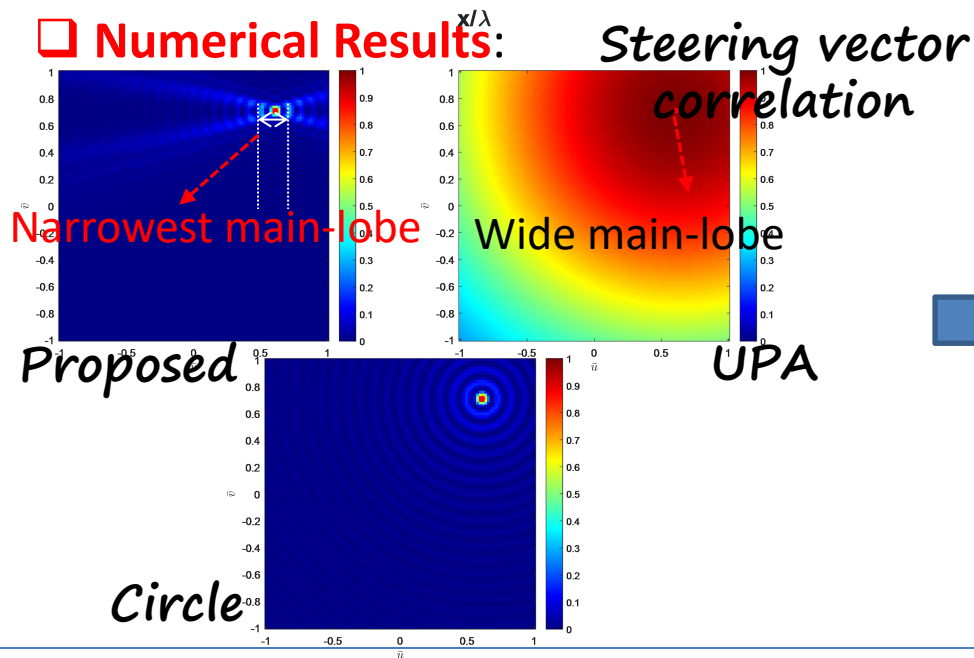
# 2D MA Sensing: Performance Evaluation

## Trajectories:

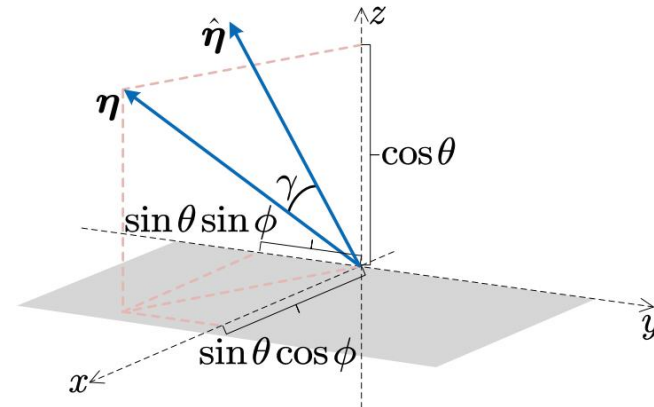
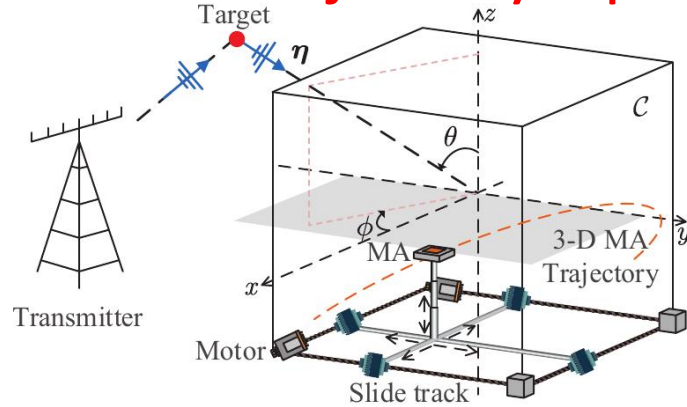


- **Proposed 2D MA trajectory**
- **UPA**: MA moves at speed  $v^m$  to form a  $\sqrt{N} \times \sqrt{N}$  UPA
- **Circle**: MA moves at speed  $v^m$  to form a circle

## Numerical Results:



# 3-D MA Trajectory Optimization for Robust Sensing



- 3-D Antenna position  $\mathbf{r}_n$  ( $n = 2, \dots, N$ ) w.r.t. its initial position  $\mathbf{r}_1$  and the velocity  $\{\mathbf{v}_n\}_{n=1}^{N-1}$ :

$$\mathbf{r}_n = \mathbf{r}_1 + T_s \sum_{m=1}^{n-1} \mathbf{v}_m$$

- Lower-bound of the mean square angular error (MSAE)  $\mathbb{E}\{\gamma^2\}$ :

$$\text{MSAEB}_x(\mathbf{R}) = \frac{\sigma^2 \lambda^2}{8\pi^2 P N |\beta|^2} \frac{\mathbf{g}^\top \mathbf{U} \mathbf{g} + \mathbf{f}^\top \mathbf{U} \mathbf{f}}{(\mathbf{f}^\top \mathbf{U} \mathbf{f})(\mathbf{g}^\top \mathbf{U} \mathbf{g}) - (\mathbf{f}^\top \mathbf{U} \mathbf{g})^2}$$

$\lambda$ : wavelength

$N$ : number of snapshots

$P/\sigma^2$ : SNR

$\beta$ : complex path coefficient

$\mathbf{f}$

$\triangleq [\cos\theta\cos\phi, \cos\theta\sin\phi, -\sin\theta]^\top$

$\mathbf{g} \triangleq [-\sin\phi, \cos\phi, 0]^\top$

$\mathbf{X} \triangleq [\theta, \phi]^\top$

$\mathbf{U} \triangleq$

$$\begin{bmatrix} \text{var}(x) & \text{cov}(x, y) & \text{cov}(x, z) \\ \text{cov}(x, y) & \text{var}(y) & \text{cov}(y, z) \\ \text{cov}(x, z) & \text{cov}(y, z) & \text{var}(z) \end{bmatrix}$$

APV covariance matrix

$\mathbf{R} = [\mathbf{r}_1, \dots, \mathbf{r}_N]$ : antenna position matrix (APM)

W. Ma, L. Zhu, X. Shao, and R. Zhang, "3-D trajectory optimization for robust direction sensing in movable antenna systems," IEEE Transactions on Wireless Communications, vol. 25, pp. 19677-19691, 2026.

# Problem Formulation

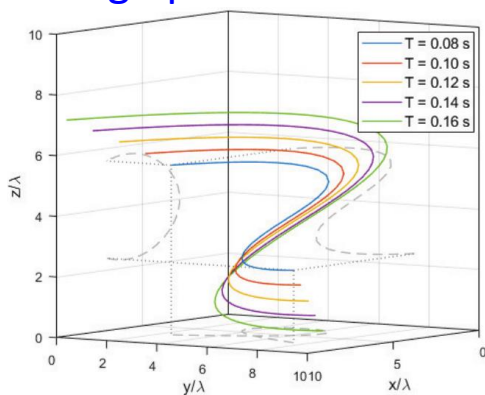
- ❑ **Objective:** Minimize the maximum  $\text{MSAEB}_\chi(\mathbf{R})$  over the angular region of interest  $\mathbb{D}$  by optimizing APM  $\mathbf{R}$  and velocity matrix  $\mathbf{V}$

$$\text{MSAEB}_\chi(\mathbf{R}) \iff \min_{\mathbf{R}, \mathbf{V}} \frac{\mathbf{g}^\top \mathbf{U} \mathbf{g} + \mathbf{f}^\top \mathbf{U} \mathbf{f}}{(\mathbf{f}^\top \mathbf{U} \mathbf{f})(\mathbf{g}^\top \mathbf{U} \mathbf{g}) - (\mathbf{f}^\top \mathbf{U} \mathbf{g})^2}$$

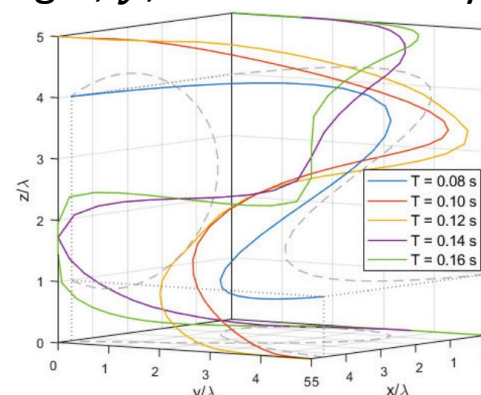
$$\begin{aligned} \min_{\mathbf{R}, \mathbf{V}, \delta} \max_{\chi \in \mathbb{D}} & \frac{\mathbf{g}^\top \mathbf{U} \mathbf{g} + \mathbf{f}^\top \mathbf{U} \mathbf{f}}{(\mathbf{f}^\top \mathbf{U} \mathbf{f})(\mathbf{g}^\top \mathbf{U} \mathbf{g}) - (\mathbf{f}^\top \mathbf{U} \mathbf{g})^2} \quad \leftarrow \text{maximum } \text{MSAEB}_\chi(\mathbf{R}) \text{ over } \mathbb{D} \\ \text{s.t. } & \|\mathbf{v}_n\|_2 \leq v^m, \quad n = 1, \dots, N-1, \quad \leftarrow \text{Maximum speed constraint} \\ & \mathbf{r}_n \in \mathcal{C}, \quad n = 1, \dots, N, \quad \leftarrow \text{Moving region constraint} \\ & \mathbf{r}_n = \mathbf{r}_1 + T_s \sum_{m=1}^{n-1} \mathbf{v}_m, \quad n = 2, \dots, N, \quad \leftarrow \text{Trajectory constraint} \end{aligned}$$

- ❑ **Solution:** Alternating optimization and SCA for optimizing  $\mathbf{x}$ ,  $\mathbf{y}$ , and  $\mathbf{z}$  iteratively

Without region  
size constraint



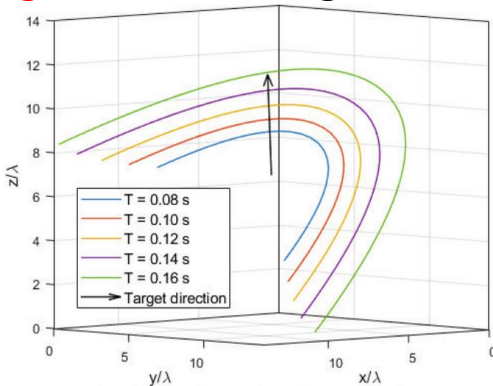
With region  
size constraint



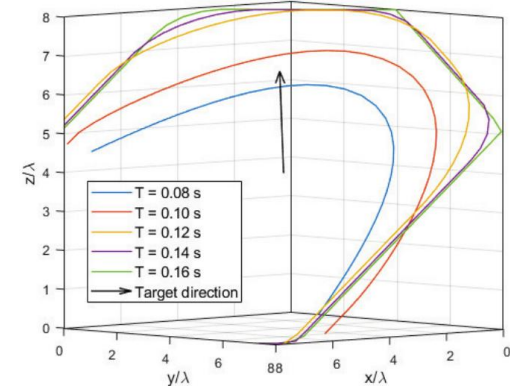
# Performance Analysis

- When  $\mathbb{D}$  contains only a single direction, the optimal MA trajectory should lie entirely in the plane orthogonal to the target direction

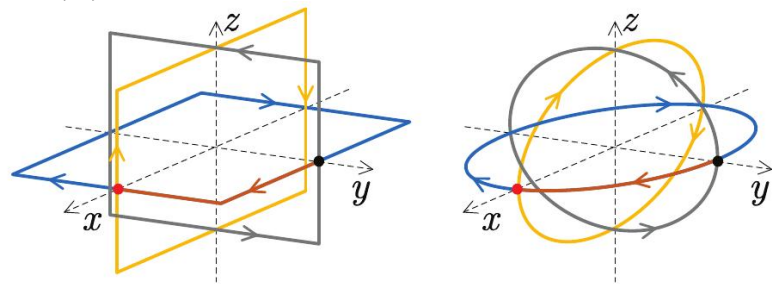
Without region size constraint



With region size constraint



- $\text{MSAEB}_\chi(\mathbf{R})$  is constant for all  $\chi \in [0, \pi] \times [0, 2\pi]$  if and only if  $\mathbf{U} = \tau \mathbf{I}_3$ , where  $\tau = \text{var}(\mathbf{x}) = \text{var}(\mathbf{y}) = \text{var}(\mathbf{z})$

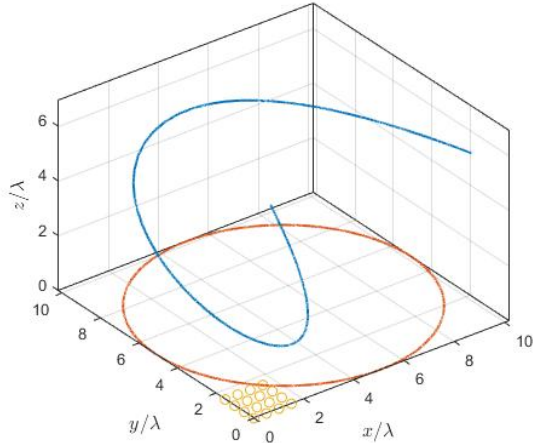


- Start/end point      — 1st segment      — 2nd segment
- Intermediate point      — 3rd segment      — 4th segment

Illustration of the isotropic MA trajectory formed by three mutually orthogonal squares or circles. Movement sequence follows the order of orange, blue, gray, and brown segments.

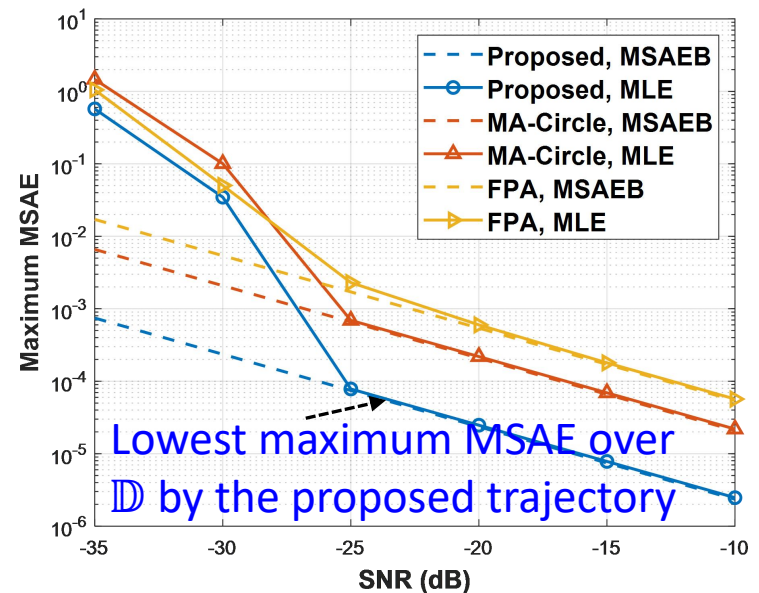
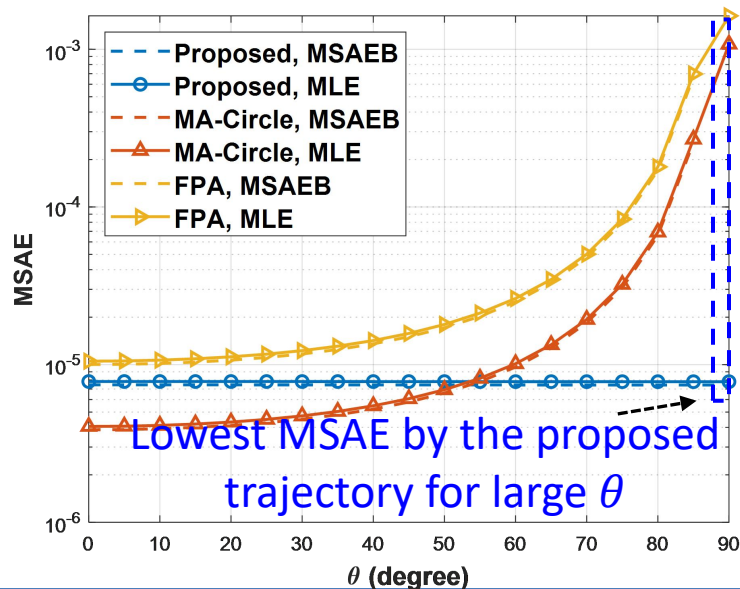
# Performance Evaluation

## □ Benchmarks:



- **Proposed 3D MA trajectory**
- **MA-Circle**: MA moves at speed  $v^m$  to form a circle
- **FPA**: The  $4 \times 4$  UPA with half-wavelength inter-antenna spacing

## □ Numerical Results:



# Outline

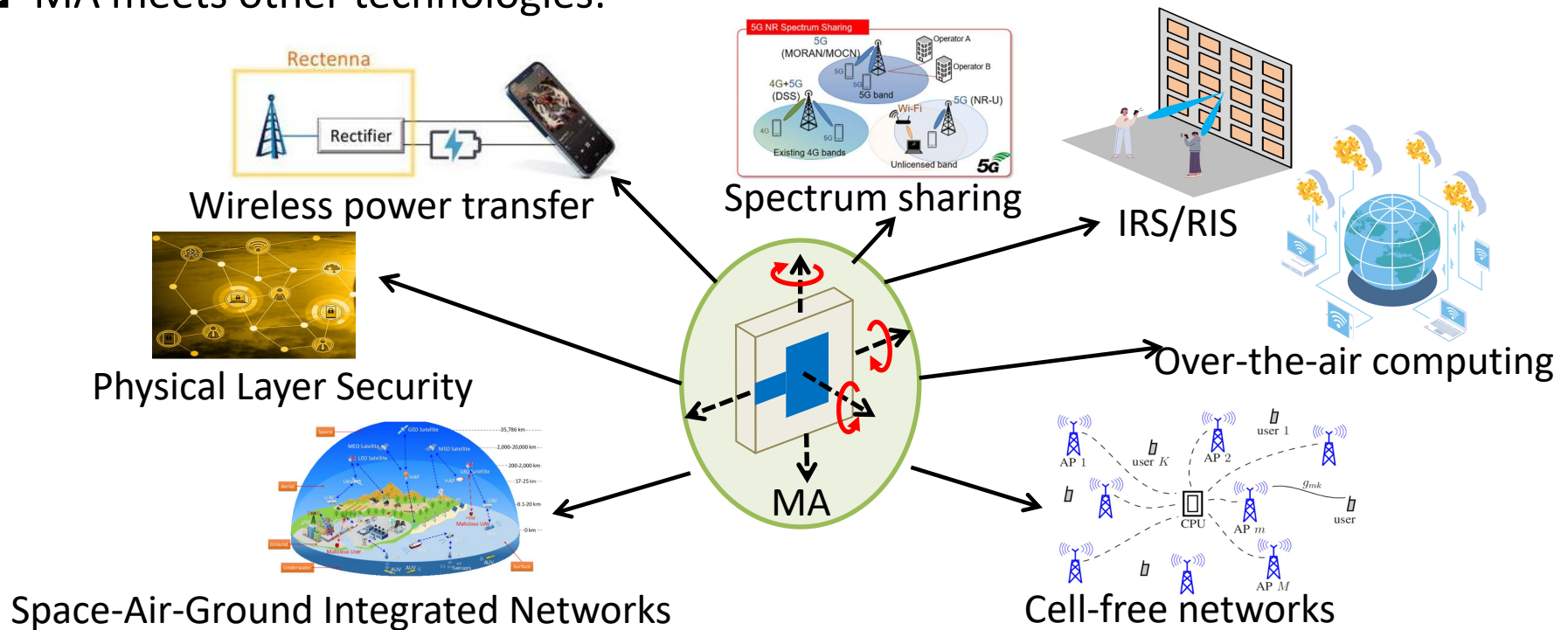
- ❑ Introduction of Movable Antenna
- ❑ MA System Design Based on Channel Statistics
- ❑ Efficient MA Architectures
- ❑ MA for Wireless Sensing
- ❑ **Conclusions and Future Directions**

## Conclusions

- ❑ MA can fully exploit the wireless channel **spatial variations (in both small and large scales)** in a confined Tx/Rx region by enabling flexible antenna **movement (position and/or rotation)**
- ❑ Leveraging **channel statistics** with a **two-timescale design** significantly reduces the overhead of frequent channel estimation and antenna repositioning, and achieves ergodic rate performance **comparable to instantaneous CSI-based designs**.
- ❑ Practical architectures offer **cost-effective and scalable deployments**. These designs effectively reduce hardware complexity while **maintaining substantial performance gains**.
- ❑ Optimizing the **discrete positions or continuous trajectories of 1D/2D/3D MAs** minimizes the **CRB** of AoA estimation MSE, and thus increase wireless sensing accuracy.

# Future Directions

- ❑ Cost-effective **implementations** of MA
- ❑ Experimental demonstrations and **field-tests** of MA systems
- ❑ **Channel measurement** and validation
- ❑ Efficient antenna **movement optimization/channel acquisition** algorithms
- ❑ **Performance analysis** for MA-aided wireless networks
- ❑ **Standardization** of MA technologies
- ❑ MA meets other technologies:





# **Movable Antennas for Wireless Communication and Sensing: Fundamental Gain and Practical Design**

**Thanks for listening!**  
**Q&A**

**Lipeng Zhu**  
**Beijing Institute of Technology**  
**24 October 2026**