

# Eliminating Blind Spots via IRS: A “Blind” Approach

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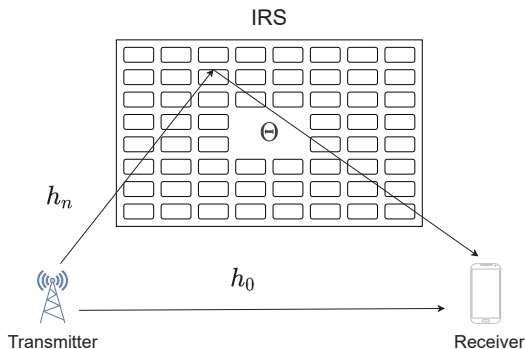
# Outline

- 1 Background
- 2 Passive Beamforming with Channel Knowledge
- 3 Passive Beamforming without Channel Knowledge
- 4 IRS Placement Optimization
- 5 Conclusion

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# What is IRS?



- Intelligent reflecting surface (IRS) is a passive reflecting device.
- Each **reflective element** induces **phase shift** in its reflected path.
- Optimize phase shifts to enhance channel, i.e., **passive beamforming**.



# An IRS prototype with 256 reflective elements



# Notation

- $N$ : number of reflective elements of IRS.
- $h_0$ : direct channel from transmitter to receiver.
- $h_n$ : reflected channel associated with the  $n$ -th reflective element.
- $\theta_n$ : phase shift of the  $n$ -th reflective element.
- $K$ : number of choices for phase shift, e.g.,  $\theta_n \in \{0, \pi\}$  if  $K = 2$ .

# Problem formulation

- Signal-to-noise ratio (SNR) is a function of  $(\theta_1, \dots, \theta_N)$ :

$$\text{SNR}(\theta_1, \dots, \theta_N) = \left| h_0 + \sum_{n=1}^N h_n e^{j\theta_n} \right|^2 P / \sigma^2.$$

- Passive beamforming seeks the optimal  $\theta_n$  to maximize SNR:

$$\begin{aligned} & \underset{\theta_1, \dots, \theta_N}{\text{maximize}} && \text{SNR}(\theta_1, \dots, \theta_N) \\ & \text{subject to} && \theta_n \in \{0, 2\pi/K, 4\pi/K, \dots, 2(K-1)\pi/K\}. \end{aligned}$$

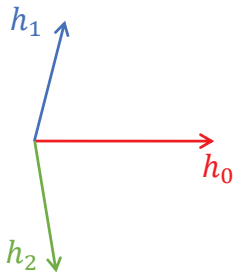
- There are totally  $2^N$  possible choices of  $(\theta_1, \dots, \theta_N)$ !

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## CPP: A simple method

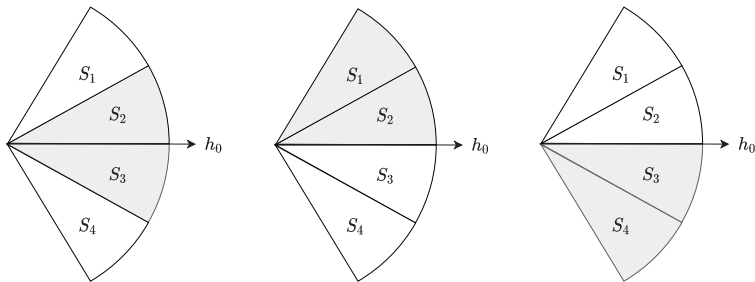
- A simple idea [Wu-Zhang, 20] is to choose  $\theta_n$  to **minimize the angle** between  $h_n e^{j\theta_n}$  and  $h_0$ , namely closest point projection (CPP).
- But CPP can give quite bad solution, e.g., when  $K = 2$ , CPP chooses  $\theta_1 = \theta_2 = 0$ . It is optimal to let  $\theta_1 = 0$  and  $\theta_2 = \pi$ .



Q. Wu and R. Zhang, "Beamforming optimization for wireless networks aided by intelligent reflecting surface with discrete phase shifts," *IEEE Trans. Commun.*, 2020.

# Enhanced CPP

- Divide complex plane into  $2K$  equal sectors, each with angle  $\pi/K$ .
- CPP rotates each  $h_n$  to within  $S_2$  or  $S_3$ , i.e., the **middle scheme**.  
Now also try out the **upper scheme** and the **lower scheme**.
- Enhanced CPP: Compare the three schemes and choose the best.



Y. Zhang, K. Shen, *et al.*, "Configuring Intelligent Reflecting Surface with Performance Guarantees: Optimal Beamforming," *IEEE J. Sel. Topics Signal Process.*, 2022.

# Approximation ratios

## Definition 1

Let  $\text{SNR}^*$  be the optimum, and let  $\text{SNR}$  be the achieved performance. If  $r \in [0, 1]$  is an approximation ratio, then

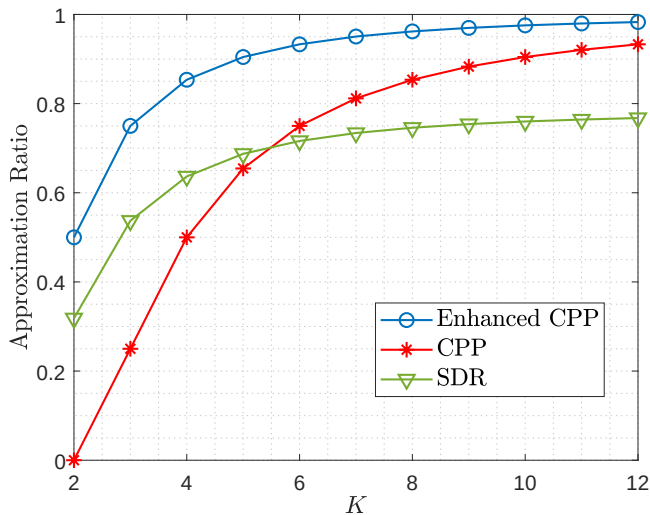
$$r \cdot \text{SNR}^* \leq \text{SNR} \leq \text{SNR}^*.$$

## Proposition 2.1

*The approximation ratios of enhanced CPP, CPP, and semidefinite relaxation (SDR) are:*

$$\begin{aligned} r_{\text{ECPP}} &= \frac{1 + \cos(\pi/K)}{2} \\ r_{\text{CPP}} &= \cos^2\left(\frac{\pi}{K}\right) \\ r_{\text{SDR}} &= \frac{K^2 \sin^2(\pi/K)}{4\pi} \end{aligned}$$

# Approximation ratios



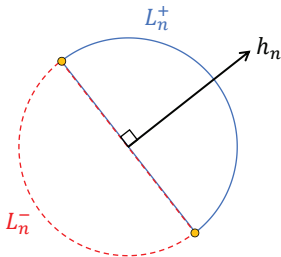


## Exact method for global optimum (1/3)

- Introduce auxiliary variable  $\mu \in \mathbb{C}$  and reformulate the problem as

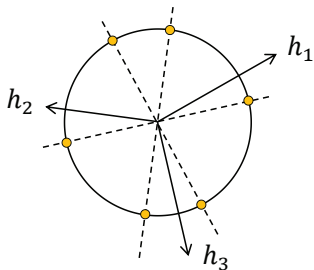
$$\begin{aligned} & \underset{x_n \in \{-1, +1\}, \mu}{\text{maximize}} && \|\mu\| \\ & \text{subject to} && \mu = h_0 + h_1 x_1 + h_2 x_2 + \dots + h_N x_N. \end{aligned}$$

- It is optimal to minimize the angle between  $h_n x_n$  and  $\mu$ .
- Geometrically,  $h_n^\top v = 0$  cuts the complex plane into two halfspaces,  $L_n^+$  and  $L_n^-$ . We have  $x_n^* = +1$  if  $\mu^* \in L_n^+$ , and  $x_n^* = -1$  otherwise.



## Exact method for global optimum (2/3)

- Cutting for every  $h_n$  divides the complex plane into  $2N$  sectors.
- Assuming  $\mu^*$  lies in a particular sector, we can immediately tell  $x_n^*$  by checking which halfspace,  $L_n^+$  or  $L_n^-$ , this sector belongs to.
- After obtaining  $\mathbf{x}$ , we compute  $\|\mu\|$  in  $O(N)$  time. Try out all sectors and pick the best, so total time is  $O(N^2)$ . Can we do even better?



S. Ren, K. Shen, X. Li, X. Chen, and Z.-Q. Luo, "A Linear Time Algorithm for the Optimal Discrete IRS Beamforming," *IEEE Wireless Commun. Lett.*, 2023.

## Exact method for global optimum (3/3)

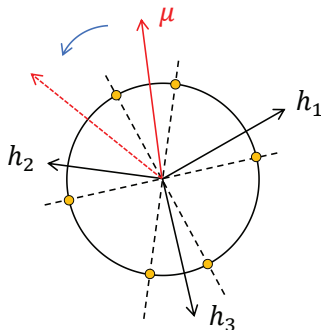
- As  $\mu$  crosses the cut line  $h_1^\top v = 0$  (from  $L_1^+$  to  $L_1^-$ ) to enter the new sector, the value of  $\mu$  can be updated as

$$\mu \leftarrow \mu - 2h_1.$$

Likewise, as  $\mu$  crosses  $h_1^\top x = 0$  from  $L_1^-$  to  $L_1^+$ , we update

$$\mu \leftarrow \mu + 2h_1.$$

- Computing  $\mu$  for the first sector +  $(2N - 1)$  updates =  $O(N)$  time.



# Halfway recap

- Passive beamforming for IRS is a discrete quadratic program (QP).
- Conventional CPP may yield very bad performance.
- Proposed enhanced CPP gives a higher approximation ratio.
- The problem can be optimally solved in linear time.

Why are we still interested in approximate methods?

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# Motivation

- Channel knowledge  $\{h_0, h_n\}$  can be **difficult to acquire** in practice:  
(i) protocol      (ii) chip      (iii) channel model
- When channels are unknown, a common idea in the literature is to choose phase shifts in a greedy fashion.
- Greedy: **Try out  $T$  random samples**  $(\theta_1, \dots, \theta_N)$ , measure their Reference Signal Received Power (RSRP), and then **pick the best one**.

# Performance of greedy method

## Proposition 3.1

For fixed  $\frac{\sum_{n=1}^N |h_n|^2}{N|h_0|^2}$ , the SNR achieved by the greedy method satisfies

$$\mathbb{E}[\text{SNR}] = \Omega(N \log T) \text{ if } T = o(\sqrt{N})$$

$$\mathbb{E}[\text{SNR}] = O(N \log T) \text{ in general}$$

where the expectation is taken over random samples of  $\theta$ .

Remark: Greedy method solely depends on the best sample and neglects the rest, so it does NOT make full use of the data.

S. Ren, K. Shen, X. Li, X. Chen, and Z.-Q. Luo, "Configuring Intelligent Reflecting Surface with Performance Guarantees: Blind Beamforming," *IEEE Trans. Wireless Commun.*, 2023.

# Conditional sample mean (CSM)

- The proposed method CSM also takes  $T$  random samples as input.
- Compute the **conditional sample mean** of RSRP:

$$\hat{\mathbb{E}}[P \mid \theta_n = \phi], \forall \phi \in \{0, 2\pi/K, \dots, 2(K-1)\pi/K\}.$$

- Choose each  $\theta_n$  to maximize the conditional sample mean:

$$\theta_n = \arg \max_{\phi} \hat{\mathbb{E}}[P \mid \theta_n = \phi].$$

V. Arun and H. Balakrishnan, "RFocus: Beamforming using thousands of passive antennas," in *USENIX Symp. Netw. Sys. Design Implementation (NSDI)*, 2020.

S. Ren, K. Shen, X. Li, X. Chen, and Z.-Q. Luo, "Configuring Intelligent Reflecting Surface with Performance Guarantees: Blind Beamforming," *IEEE Trans. Wireless Commun.*, 2023.



## A toy example with $K = 2$ , $N = 4$ , and $T = 6$

| $t$      | 1                | 2              | 3                    | 4                    | 5                    | 6                  |
|----------|------------------|----------------|----------------------|----------------------|----------------------|--------------------|
| $\theta$ | $(0, \pi, 0, 0)$ | $(0, 0, 0, 0)$ | $(\pi, \pi, \pi, 0)$ | $(\pi, 0, \pi, \pi)$ | $(\pi, \pi, 0, \pi)$ | $(0, 0, \pi, \pi)$ |
| $P$      | 2.8              | 1.0            | 1.5                  | 3.3                  | 0.3                  | 0.4                |

- Let us see how to decide  $\theta_1$ :

- ▶ Compute the average power conditioned on  $\theta_1 = 0$ :

$$\widehat{\mathbb{E}}[P \mid \theta_1 = 0] = (2.8 + 1.0 + 0.4)/3 = 1.4.$$

- ▶ Compute the average power conditioned on  $\theta_1 = \pi$ :

$$\widehat{\mathbb{E}}[P \mid \theta_1 = \pi] = (1.5 + 3.3 + 0.3)/3 = 1.7.$$

- ▶ Since  $1.7 > 1.4$ , set  $\theta_1 = \pi$ .

- We obtain  $(\pi, 0, \pi, 0)$ , which does NOT appear in random samples.

# Performance of CSM

## Proposition 3.2

For fixed  $\frac{\sum_n |h_n|^2}{N|h_0|^2}$ , CSM recovers the solution of enhanced CPP, and yields

$$\mathbb{E}[\text{SNR}] = \Theta(N^2) \text{ if } T = \Omega(N^2(\log N)^3) \text{ and } K > 2,$$

where the expectation is taken over random samples of  $\theta$ .

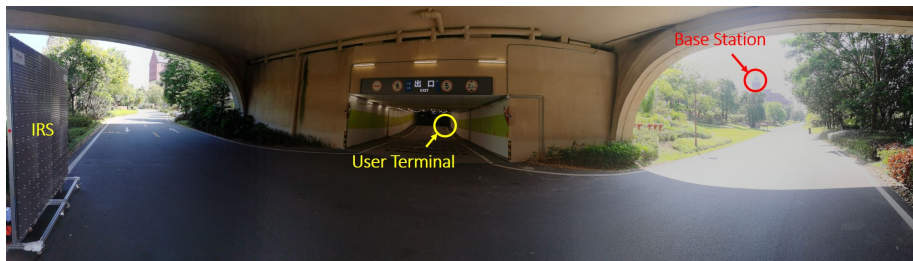
Remark:  $\Theta(N^2)$  is also an upper bound on SNR, so CSM is optimal!

S. Ren, K. Shen, X. Li, X. Chen, and Z.-Q. Luo, "Configuring Intelligent Reflecting Surface with Performance Guarantees: Blind Beamforming," *IEEE Trans. Wireless Commun.*, 2023.

# Setting

- 200 MHz centered at 2.6 GHz
- $N = 256$
- $K = 4$  with each  $\theta_n \in \{0, \pi/2, \pi, 3\pi/2\}$
- $T = 10N$
- Aside from CSM and enhanced CSM, consider two baselines:
  - ▶ Fixed Method: fix each  $\theta_n$  at zero
  - ▶ Greedy Method: pick the best random sample

# Underground parking-lot



**Figure:** A panoramic view of the field test site. The base station is located on a 20-meter-high terrace while the user terminal is located inside an underground parking lot. The IRS is placed at the entrance of the parking lot. The IRS is approximately 250 meters away from the base station, and the user terminals are approximately 40 meters away from the IRS.

# Underground parking-lot



# Underground parking-lot

**Table:** Average Performance of the Various Algorithms

| Algorithm    | RSRP Boost (dB) | SINR Boost (dB) |
|--------------|-----------------|-----------------|
| CSM          | 4.02            | 3.57            |
| Enhanced CSM | 4.62            | 3.81            |
| Greedy       | -3.93           | -3.84           |
| Fixed        | -1.69           | -1.69           |

# Extension for multiple IRSs

## Proposition 3.3

When there are  $L$  IRSs, running CSM *sequentially* across these IRSs yields

$$\mathbb{E}[\text{SNR}] = \Theta(N^{2L})$$

provided that

- $T = \Omega(N^2(\log N)^3)$ ;
- $K \geq 2L - 1$ .

In contrast, the previous optimality condition [Mei-Zhang, 21] requires

- channels are known perfectly;
- $K \rightarrow \infty$  (so phase shifting is continuous).

F. Xu, J. Yao, W. Lai, K. Shen, X. Li, X. Chen, and Z.-Q. Luo, "Coordinating Multiple Intelligent Reflecting Surfaces without Channel Information," *IEEE Trans. Signal Process.*, 2024.

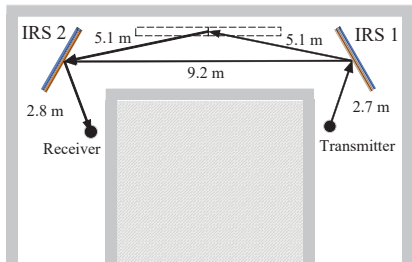
W. Mei and R. Zhang, "Cooperative beam routing for multi-IRS aided communication," *IEEE Wireless Commun. Lett.*, 2021.

# Multi-IRS System

- Number of random samples:  $T = 1000L$
- Following three IRSs are used:
  - ▶ IRS 1:  $N = 294, \theta_n \in \{0, \pi\}$
  - ▶ IRS 2:  $N = 294, \theta_n \in \{0, \pi\}$
  - ▶ IRS 3:  $N = 64, \theta_n \in \{0, \pi/2, \pi, 3\pi/2\}$
- We test the following methods:
  - ▶ Fixed: fix each  $\theta_n$  at zero
  - ▶ Greedy: pick the best out of  $T$  random samples
  - ▶ Virtual Single-IRS: treat multiple IRSs as a single IRS and run CSM
  - ▶ Sequential CSM: perform CSM sequentially across IRSs

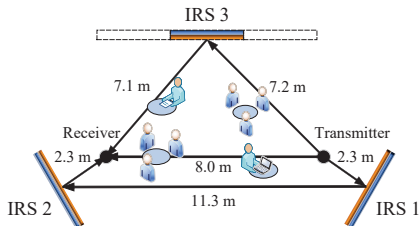


# Indoor hallway



- Deploy IRS 1 and IRS 2 in a U-shaped office building hallway.

# Outdoor café

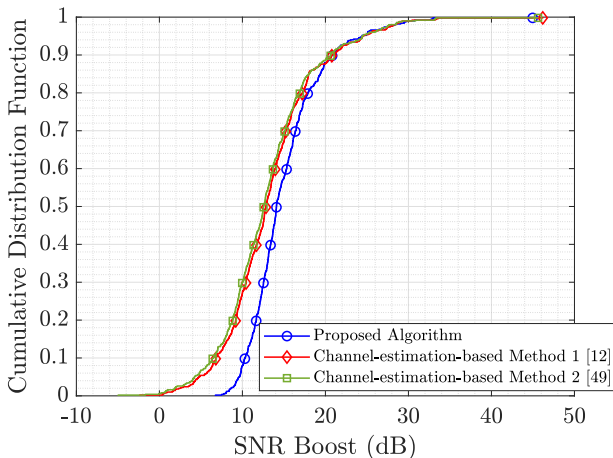


- Deploy three IRSs alongside an open café.

# Test results in multi-IRS systems

| Method             | SNR Boost (dB) |       |
|--------------------|----------------|-------|
|                    | Hallway        | Café  |
| Fixed              | 2.74           | 2.91  |
| Greedy             | 5.33           | 8.48  |
| Virtual Single-IRS | 12.07          | 10.80 |
| Sequential CSM     | 17.08          | 14.09 |

# Blind beamforming vs. channel estimation



Y. Han, S. Zhang, L. Duan, and R. Zhang, "Cooperative double-IRS aided communication: Beamforming design and power scaling," *IEEE Wireless Commun. Lett.*, 2020.

Y. Han, S. Zhang, L. Duan, and R. Zhang, "Double-IRS aided MIMO communication under LoS channels: Capacity maximization and scaling," *IEEE Trans. Commun.*, 2022.

# Extension for multiple receivers

## Proposition 3.4

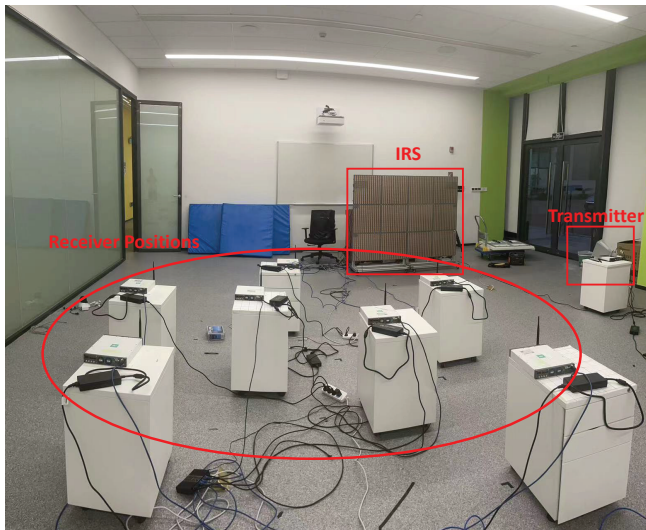
Assume that  $U$  receivers are uniformly distributed. Every receiver finds its desirable  $(\theta_1, \dots, \theta_N)$  by running CSM individually. Then decide  $\theta_n$  by **majority voting**. If  $T = \Omega(N^2(\ln NU)^3 + N^2U(\ln NU))$  and  $N = \omega(U^2)$ , then this method yields

$$\mathbb{E}[\text{SNR}] = \frac{4Pc_u^2}{\sigma^2\pi^2} \cdot \Omega\left(\frac{N^2}{U}\right) \quad (1)$$

for all receivers.

F. Xu, J. Yao, W. Lai, K. Shen, X. Li, X. Chen, and Z.-Q. Luo, "Blind beamforming for coverage enhancement with intelligent reflecting surface", *IEEE Trans. Wireless Commun.*, 2024.

# Broadcast transmission in office



# Broadcast transmission in office

Table: Minimum SNR (in Decibel) among  $U$  receivers.

| Methods           | $N = 588$ |         |         | $N = 294$ |         |         |
|-------------------|-----------|---------|---------|-----------|---------|---------|
|                   | $U = 5$   | $U = 6$ | $U = 7$ | $U = 5$   | $U = 6$ | $U = 7$ |
| MV-CSM            | 8.54      | 7.45    | 6.95    | 7.13      | 6.03    | 5.39    |
| P-CSM             | 5.10      | 5.81    | 4.08    | 4.69      | 3.35    | 2.53    |
| Position-Based    | 4.06      | 3.13    | 2.94    | 2.82      | 2.75    | 2.21    |
| Neural + SDR      | 5.88      | 4.65    | 3.66    | 5.06      | 4.68    | 2.50    |
| Neural + Gradient | 4.16      | 3.23    | 2.58    | 4.03      | 4.80    | 1.69    |
| Greedy            | 5.21      | 5.21    | 5.21    | 4.93      | 4.94    | 4.96    |
| EMS               | 5.13      | 5.13    | 5.13    | 4.62      | 4.66    | 4.64    |
| Zero Phase Shift  | 1.82      | 1.82    | 1.82    | 1.35      | 1.35    | 1.35    |
| Without IRS       | 0.86      | 0.86    | 0.86    | 0.86      | 0.86    | 0.86    |

# Broadcast transmission in office

Table: Running Time (in sec) of Different Methods

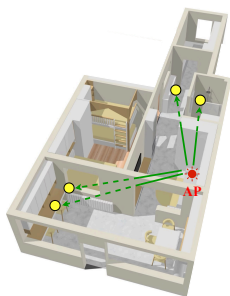
| Methods           | $N = 588$ |         |         | $N = 294$ |         |         |
|-------------------|-----------|---------|---------|-----------|---------|---------|
|                   | $U = 5$   | $U = 6$ | $U = 7$ | $U = 5$   | $U = 6$ | $U = 7$ |
| MV-CSM            | 5.9       | 7       | 10.4    | 2.2       | 2.8     | 3.6     |
| P-CSM             | 2.6       | 2.8     | 3.1     | 1.2       | 1.4     | 1.8     |
| Position-based    | 60.2      | 69.1    | 74.5    | 51.3      | 56.1    | 67.4    |
| Neural + SDR      | 84.9      | 98.3    | 114.6   | 46        | 55.2    | 62.6    |
| Neural + Gradient | 37.1      | 42.3    | 50.5    | 28.2      | 34.8    | 40.1    |
| Greedy            | 1.2       | 1.7     | 2.2     | 1.1       | 1.6     | 1.8     |
| EMS               | 1.3       | 1.7     | 2.1     | 1.1       | 1.5     | 1.9     |



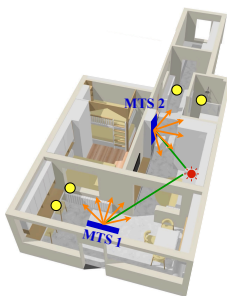
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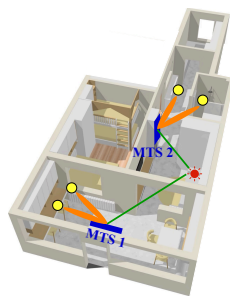
# Using IRSs to eliminate blind spots



(a) original case



(b) IRS placement



(c) phase shifting

- Blind spots are non-uniformly distributed in wireless environment.
- We aim to eliminate blind spots by placing IRSs properly.

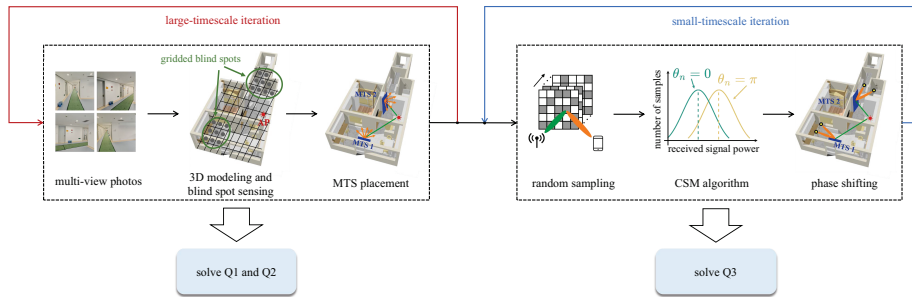
# Key questions

**To remove blind spots, we must answer:**

- Q1: How many IRSs are needed?
- Q2: Where are these RISs placed?
- Q3: How to coordinate phase shifts? (Ans: Run CSM across IRSs.)

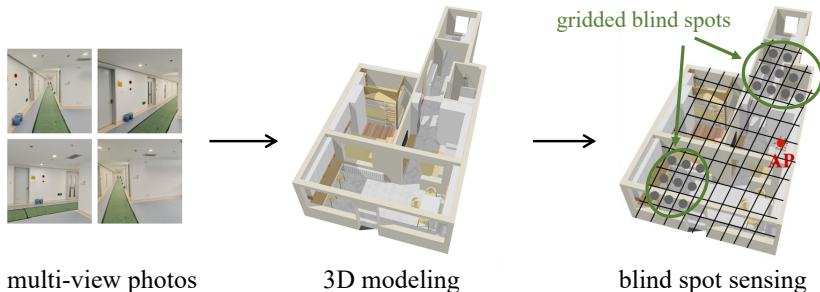
**We aim to solve Q1–Q3 in the absence of channel knowledge.**

# Two-timescale configuration



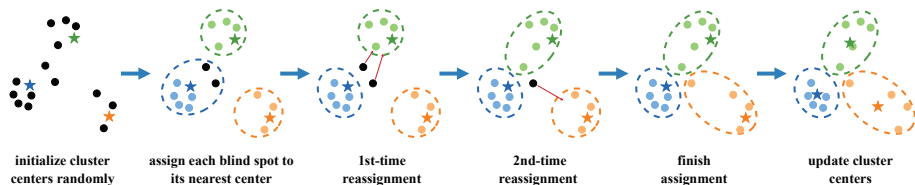
- Visual images are used for **long-run** IRS placement.
- RSRP data are used for **short-run** phase shifting.

# 3D-modeling and blind-spot prediction



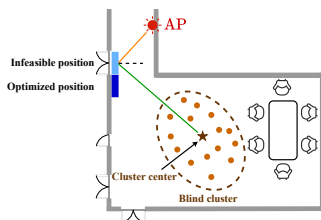
- Construct 3D model from multi-view photos.
- Predict blind spots by ray tracing.

# Blind spot clustering



- For  $M$  IRSs, we divide blind spots into  $M$  clusters by K-means.
- But each IRS can handle at most  $C$  blind spots.
- We modify K-means to account for the cluster size constraint.

# Proposed RFZero scheme

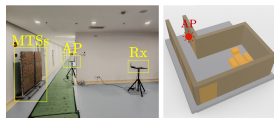


- Start from  $M = 1$ .
- Run blind spot clustering.
- Place each IRS so that reflected path passes through cluster center. (Round it to the nearest feasible position if needed.)
- Increase  $M$  until all blind spots vanish.

# Field Tests



(a) Scenario I



(b) Scenario II

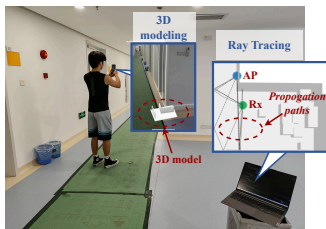


(c) Scenario III

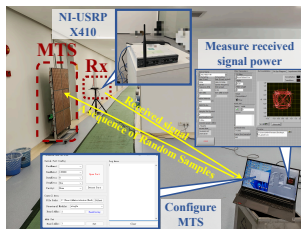
- Three indoor areas, each about 100 m<sup>2</sup>.
- Blind-spot threshold:  $\delta = -78$  dBm.



# Field Tests



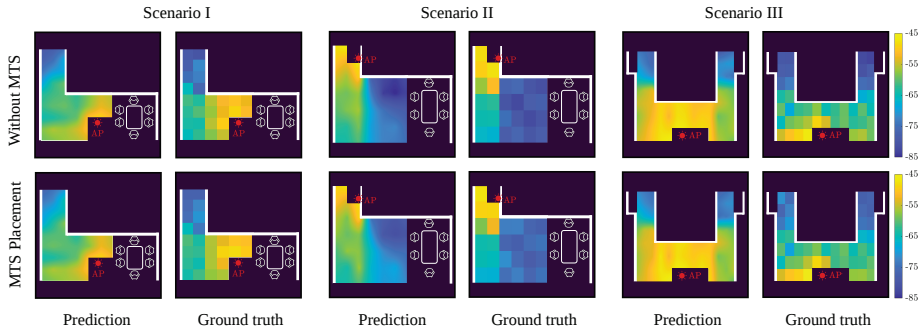
Phase I: MTS Placement



Phase II: Phase Shifting

- IRS model:  $21 \times 14 = 294$  reflective elements.
- $K = 2$ ,  $\theta_n \in \{0, \pi\}$ .
- Two NI-USRP X410 as the AP and the receiver devices.
- Sionna platform is used for ray tracing.

# Blind spot prediction



# Benchmarks

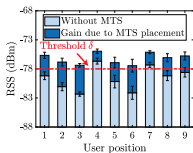
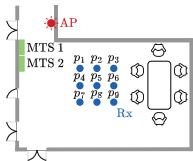
- AutoMS [Zheng et al., 24]: Exhaustive search based on gridded map.
- Gradient [Chien et al., 24]: Build channel model, and then optimize IRS placement by gradient.
- Greedy [Chen et al., 23]: Place IRSs and decide their phase shifts in a greedy fashion.

R. Ma, S. Zheng, H. Pan, L. Qiu, X. Chen, L. Liu, Y. Liu, W. Hu, and J. Ren, "AutoMS: Automated service for mmWave coverage optimization using low-cost metasurfaces," in *Proc. 30th Annu. Int. Conf. Mobile Comput., Netw. (MobiCom)*, 2024.

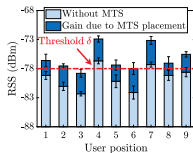
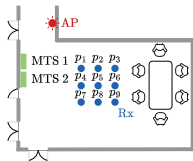
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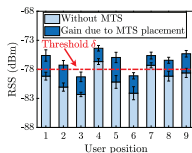
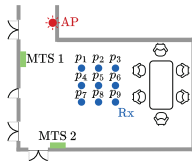
# Blind spot elimination



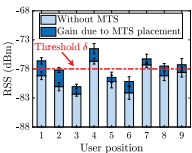
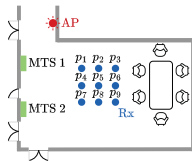
(a) RFZero



(b) AutoMS

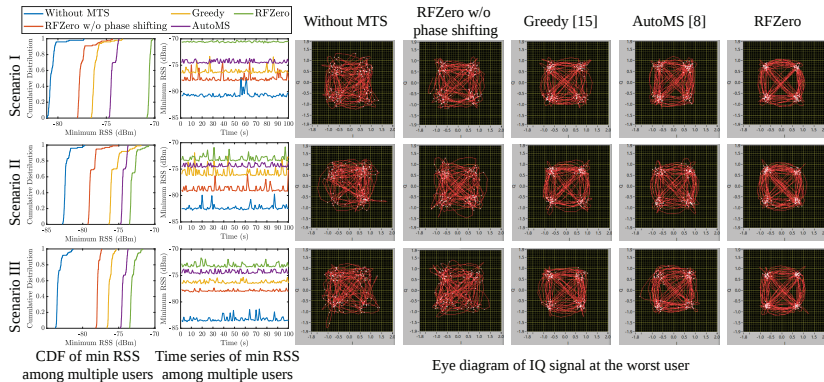


(c) Gradient-based



(d) Greedy

# Further enhancement after phase shifting



# Outline

- 1 Background
- 2 Passive Beamforming with Channel Knowledge
- 3 Passive Beamforming without Channel Knowledge
- 4 IRS Placement Optimization
- 5 Conclusion

# Conclusion

- IRS passive beamforming is a discrete QP, which can be solved by exact method or approximate method when channels are known.
- When channels are unknown, we propose CSM that recovers the solution of approximate method from  $T$  RSRP measurements.
- Number of IRSs and their placements can be blindly determined based on visual images.

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