

# MetaEverything: Intelligent MetaMaterial aided Sensing and Communications

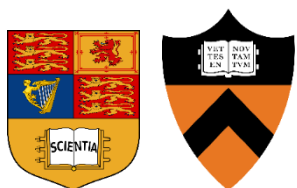
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Slides available at:

<http://wireless.egr.uh.edu/research.htm>



# Objectives

- To introduce RIS basics and potential RIS applications
  - Communication/Internet of Things
- To learn related mathematical tools to integrate RIS into future networks
  - Optimization and machine learning
- To understand how to optimize RIS aided networks
  - Communication: beamforming and deployment
  - Sensing: actively design multiple paths
  - Localization: enlarge differences

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## 1. Background

- 6G Communications and Requirements
- RIS Basics and Potential Applications

## 2. Mathematical Tools

- Optimization Theory
- Machine Learning

## 3. RIS-aided Cellular Communications

- Limited Phase Shifts Effect
- Size Effect
- Orientation and Localization
- RIS aided Multi-User Communications
- Intelligent Omni-Surface

## 4. RIS-aided RF Sensing

- Posture Recognition
- RF 3D Sensing
- Indoor Localization

# Moving Towards 6G: Emerging Use Cases

## VR/AR



AR for surgery

## Internet-of-Things



Auto-manufacturing

## Intelligence



Smart home



VR for education

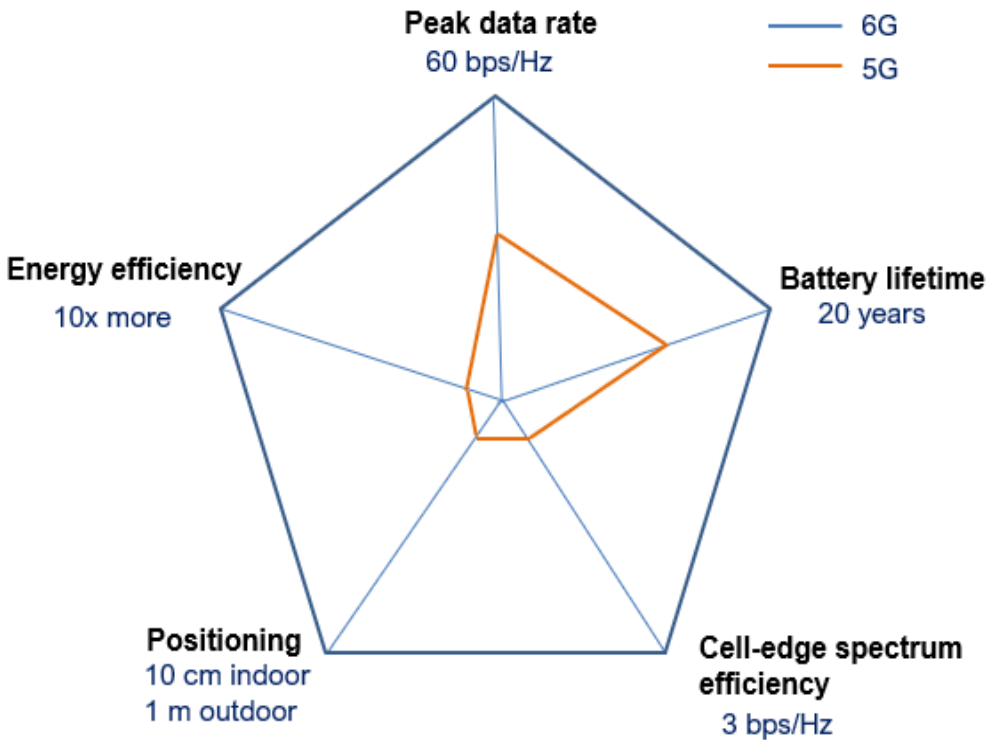


E-health



Environment sensing

# General 6G KPI Targets



*Data source: 6G White Paper, University of Oulu*



**Higher data rates**



**Lower power consumption**



**Larger Coverage**

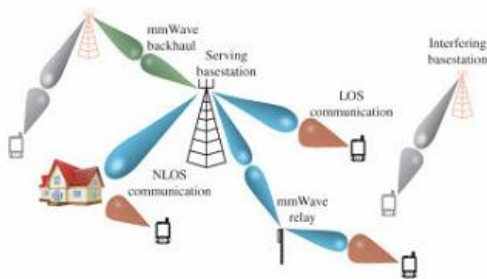


**Smarter devices**

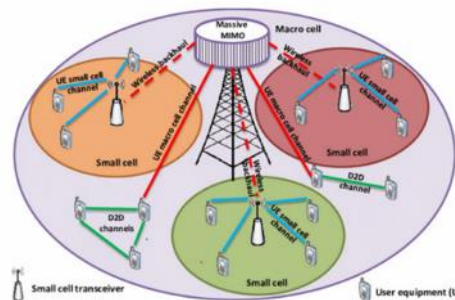
# 6G Challenges: Cost Efficiency

## 1. Conflict between low hardware cost and high data rate

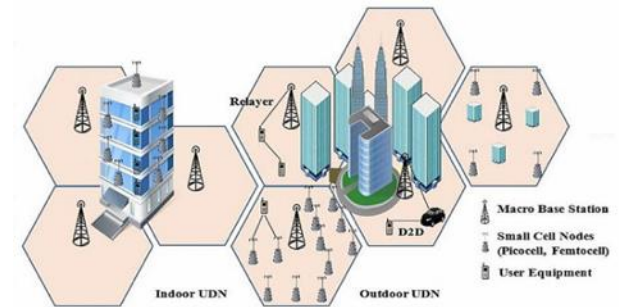
- High spatial resolution at a cost of **expensive hardware**
  - **High-frequency communication**: dedicated RF chains lead to an rapidly increasing cost as the number of users grows
  - **Massive-MIMO**: a huge number of antennas each with a phase shifter imposes significant cost in network deployment.
  - **UD-Networking**: a dense topology requires extremely high cost of deployment and coordination



**High-Frequency Communications**



**Massive MIMO**

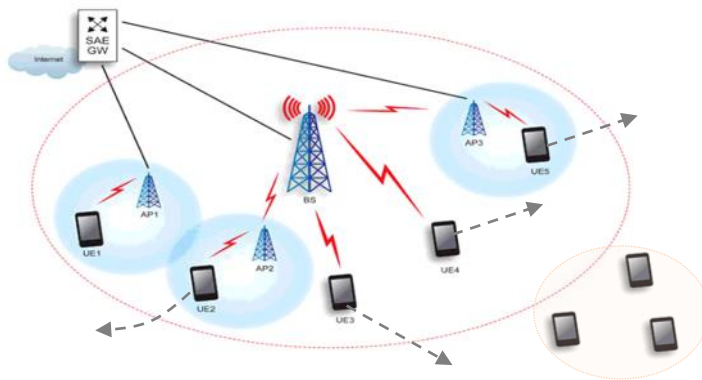


**Ultra-Dense Networking**

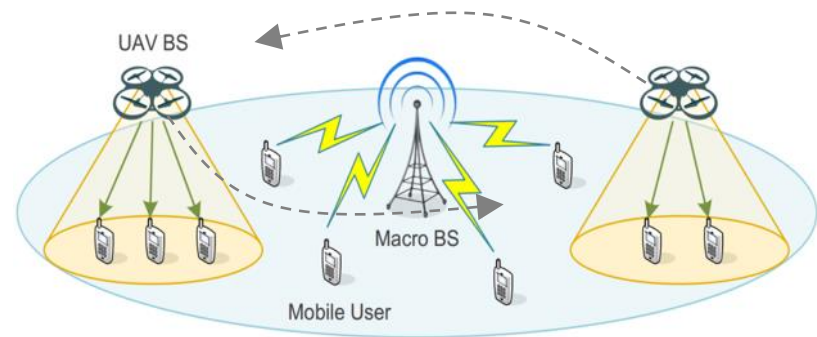
# 6G Challenges: Energy Efficiency

## 2. Conflict between flexible network deployment and low power consumption

- Fixed access points
  - No guarantee to adapt to **dynamic user traffic**
- Moving access points
  - Involve **high energy consumption** (e.g., propulsion energy and transmission energy consumption)



**Fixed access points**



**Moving access points**

# 6G Challenges: Sensing Efficiency

## 3. Conflict between simplicity&comfort and high sensing accuracy

- WiFi based RF Sensing
  - Requires the cooperation of multiple WiFi access points to achieve high sensing accuracy
- mmWave Radar
  - High hardware cost makes it hard for mass deployment



**WiFi based RF Sensing**



**mmWave Radar**



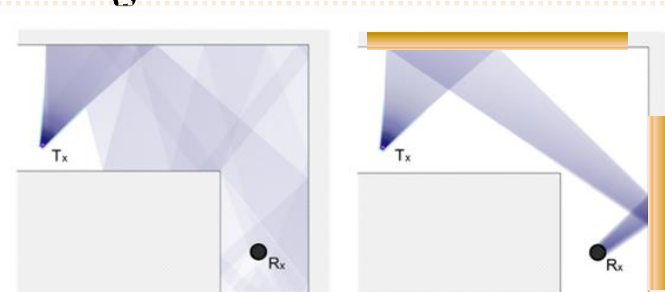
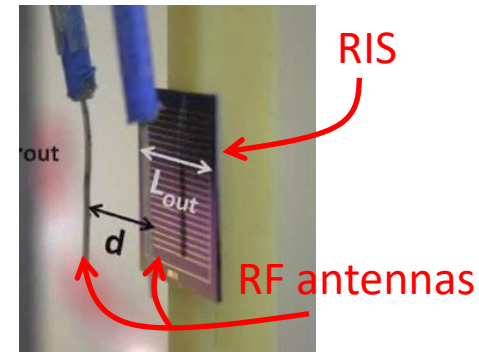
# Solutions: Meta-Material aided Sensing and Communications

## Expectation on a new technology

- Low cost in manufacture
- Easy and flexible deployment
- Compatible with 6G demands on **communications and sensing**

## Reconfigurable Meta-surfaces

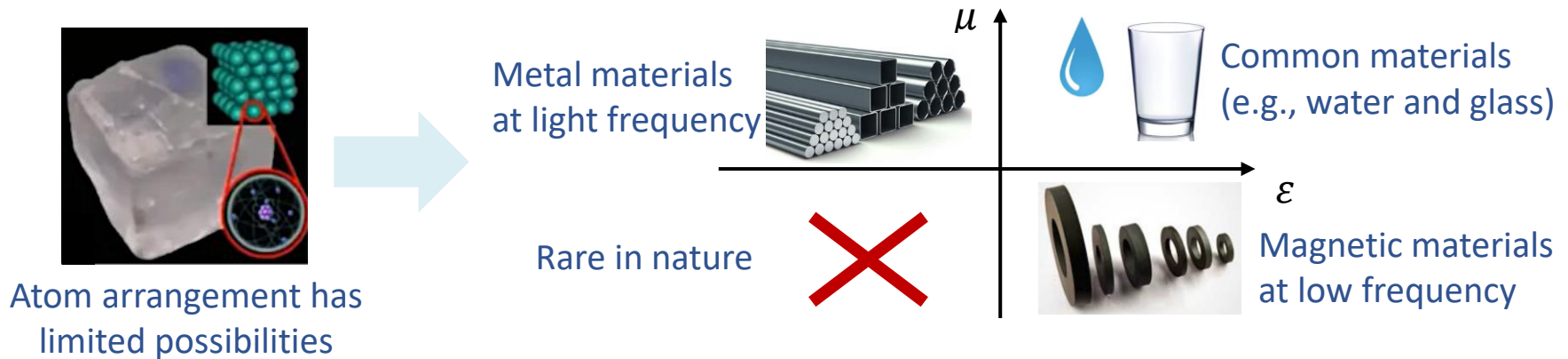
- Implemented by **metamaterial**
- Cost efficient in manufacture and deployment
- Control and customize favorable radio environments
- Provide high accuracy contact/contactless sensing with wireless data gathering
- So-called Reconfigurable Intelligent Surface or Intelligent Reflecting Surface



# Introduction of Metamaterial

## Natural Materials: Limited EM Wave Control Capability

- The *dielectric permittivity*,  $\epsilon$ , and *magnetic conductivity*,  $\mu$ , of materials determine the capability of controlling EM waves (e.g. reflection, refraction)
- Limited possibilities of atom arrangement of natural materials lead to limited available values of  $\epsilon$  and  $\mu$ , and thus limited capability to control EM waves



## Metamaterials: Powerful EM Wave Control Capability

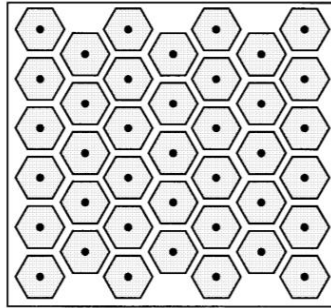
- Metamaterials are **artificial structures** that are non-existent in nature and can have **arbitrary pair of  $(\epsilon, \mu)$**
- Two technology fields studying metamaterials – **Optics** and **Microwave**

# History of Metamaterial Development



**Veselago.** Concept of Left-handed material

- $\epsilon < 0, \mu < 0$
- Negative refraction



**Sievenpiper.** Proposal of meta-surface

- Two-dimensional
- Simplify design and manufacturing



**D. R. Smith.** Experimental verification

- Left-handed material

1968

1996 & 1999

1999

2001

2001

2006

**Pendry.** Realize  $-\epsilon$  and  $-\mu$

- $-\epsilon$ : periodic array of metallic rods
- $-\mu$ : periodic array of split ring



**Sievenpiper.**

Programmable metasurface

- Varactor
- $360^\circ$  reflection phase tuning

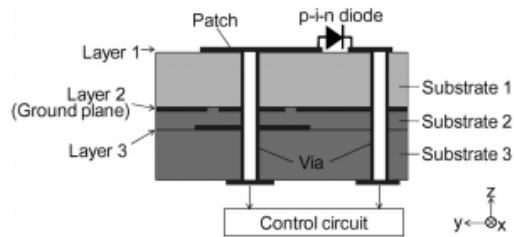


**Pendry, et al.**

Transformation optics

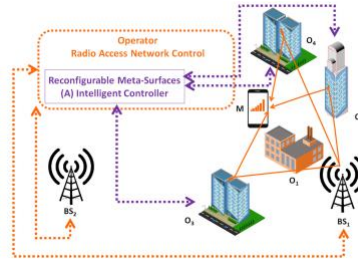
- Design metamaterial with any  $\epsilon$  and  $\mu$
- Enabling flexible control of EM wave

# History of Metamaterial Development



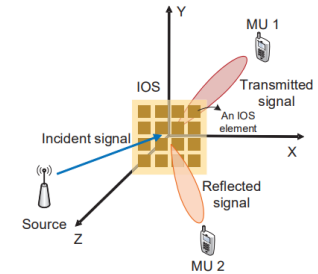
**H. Kamoda, et al.**  
Reconfigurable large reflectarray with PIN diodes

- Easy to control
- Millimeter wave



**M. D. Renzo, et al.**  
Proposal of reconfigurable intelligent surfaces

- Focus on reflection
- Extensive applications in wireless networks



**S. Zhang, et al.**  
Proposal of intelligent omni-surface

- Enabling dual function of reflection and transmission

2011

2014

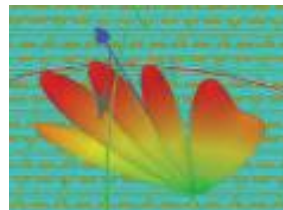
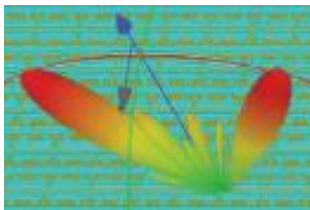
2019

2019

2020

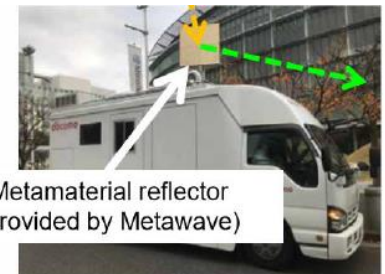
**T. Cui, et al.** Programmable metasurface with PIN diodes

- Simplify the design
- Digital coding



**NTT Docomo.**  
Prototype of metamaterial reflector

- 10x increase in data rate

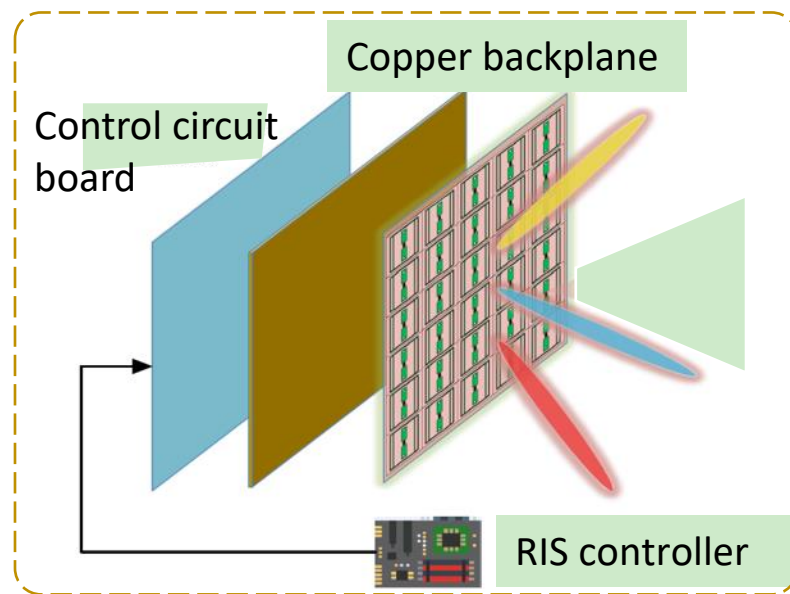


Metamaterial reflector (provided by Metawave)

# Reconfigurable Intelligent Surfaces (RIS)

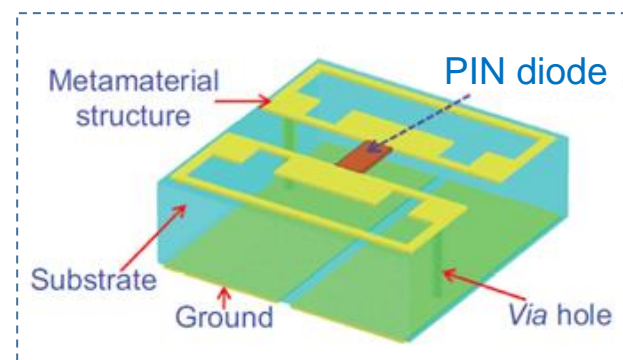
An **ultra-thin** metasurface composed of multiple layers

- **Outer layer:** A 2D-array of RIS elements; directly interact with incident signals.
- **Middle layer:** A copper plate; prevent the signal energy leakage.
- **Inner layer:** A printed circuit; connect the RIS elements to the RIS controller.



## RIS element

- Low-cost sub-wavelength **programmable metamaterial particle**.
- **Reflect** incident RF signals and **impose a controllable phase shift**
- Working frequency: from sub-6 GHz to THz



Example of a programmable metamaterial particle

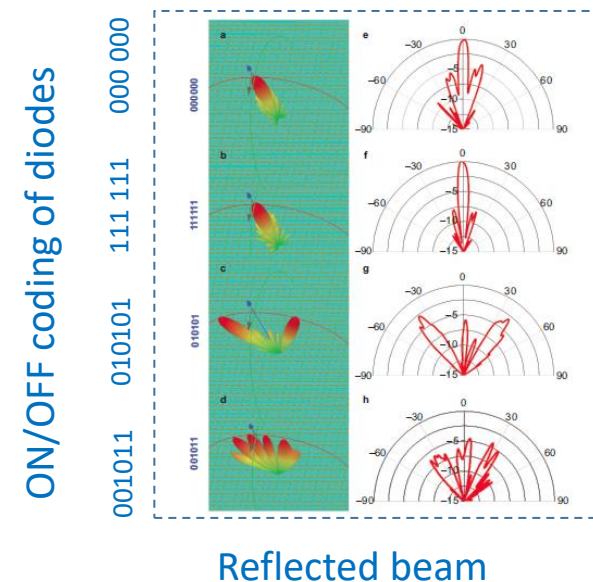
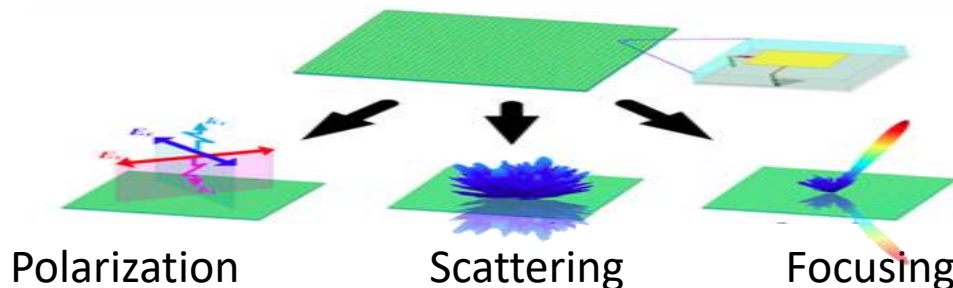
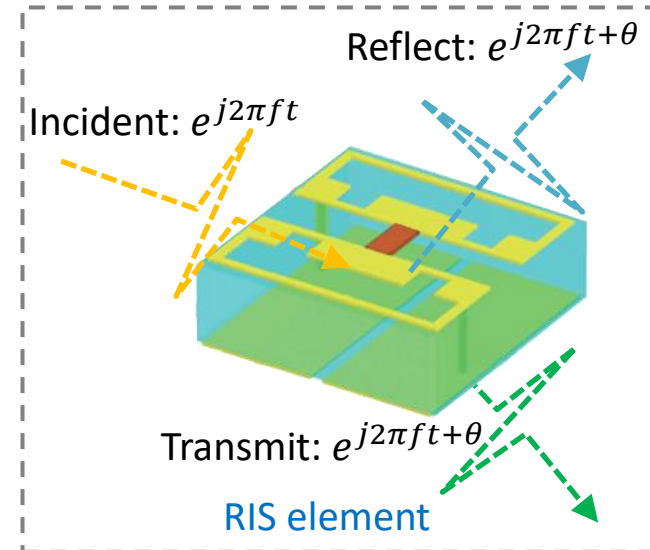
# Working Principle for Wireless Communications

## RIS works as a beamformer

- Signals can be **reflected** or **transmitted**
- Phase shift of the radiation is controlled by PIN diodes' bias voltages (**ON/OFF of the diode**)
- Programming the ON/OFF of all diodes collectively realize different beamforming modes

## Advantage

- Cost efficiency: Analog beamforming, **no extra RF chains** needed for demodulation & modulation
- **Energy Efficiency**: No extra RF signals generation, energy saving

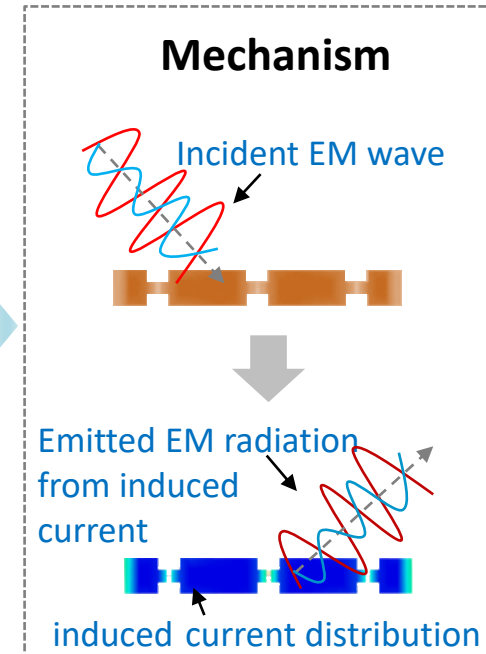
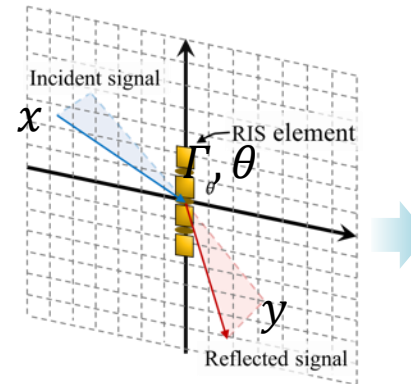


# Signal Reflection Model

## Model of reflected signal on an RIS element

$$y = \Gamma e^{j\theta} x$$

- $\Gamma \in [0,1]$ : **reflection amplitude**
  - $\Gamma = 0$ : absorbed
  - $\Gamma = 1$ : fully reflected
- $\theta \in [0,2\pi]$ : **phase shift** between incident and reflected signals.
- In practical systems, available phase shifts of an RIS element are **discrete**, due to limited number of PIN diodes ( $K$  PIN diodes  $\Rightarrow 2^K$  phase shifts).
- The parameters of an RIS element<sup>1</sup> are carefully designed so that the phase shifts have uniform intervals.



<sup>1</sup>: e.g., shape of the metal patch and type of the PIN diodes

# Channel Model

## Rician Model

- User-RIS-BS links act as the dominant LoS component
- All other paths contributes the NLoS

$$\tilde{h}_{m,n} = \sqrt{\frac{\kappa}{\kappa+1}} \underbrace{h_{m,n}}_{\text{LoS}} + \sqrt{\frac{1}{\kappa+1}} \underbrace{\hat{h}_{m,n}}_{\text{NLoS}}$$

Ratio of LoS to NLoS

- Product of distance path loss

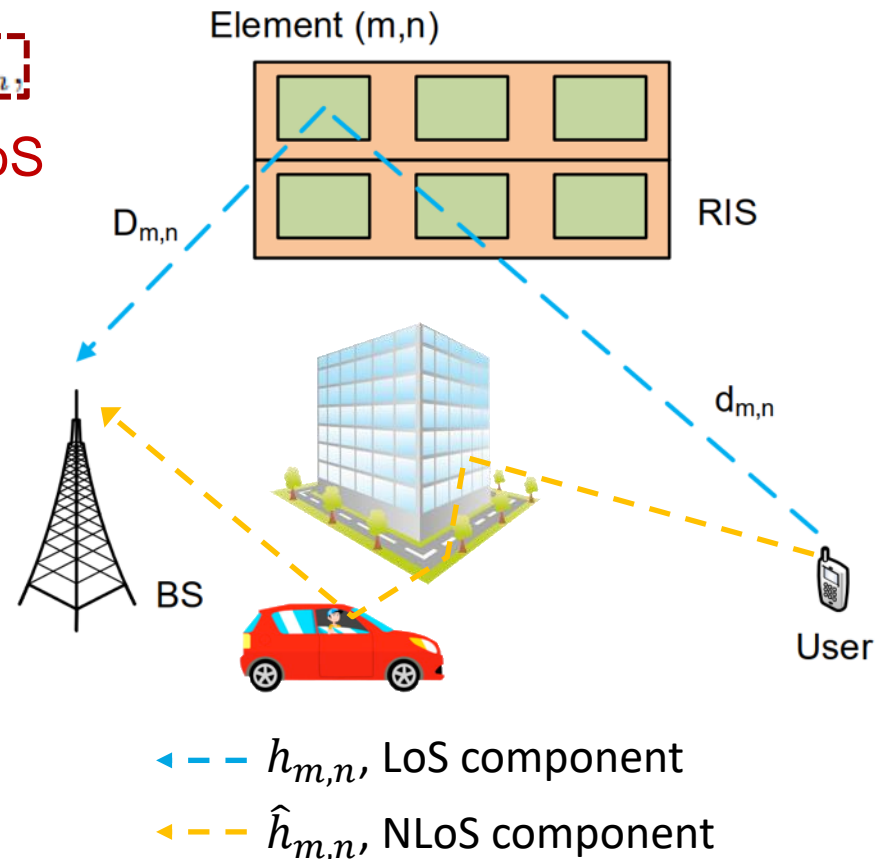
$$|h_{m,n}|^2 \propto d_{m,n}^{-\alpha} D_{m,n}^{-\alpha}$$

$$|\hat{h}_{m,n}|^2 \propto d_{m,n}^{-\alpha} D_{m,n}^{-\alpha}$$

- Received signal

$$y = \sum_{m,n} \underbrace{\Gamma}_{\text{Reflection coefficient}} e^{j\theta_{m,n}} \underbrace{\tilde{h}_{m,n}}_{\text{Channel gain}} x + \underbrace{w}_{\text{noise}}$$

Reflection coefficient    Channel gain





# Applications: Wireless Communications

## Spectrum efficiency enhancement

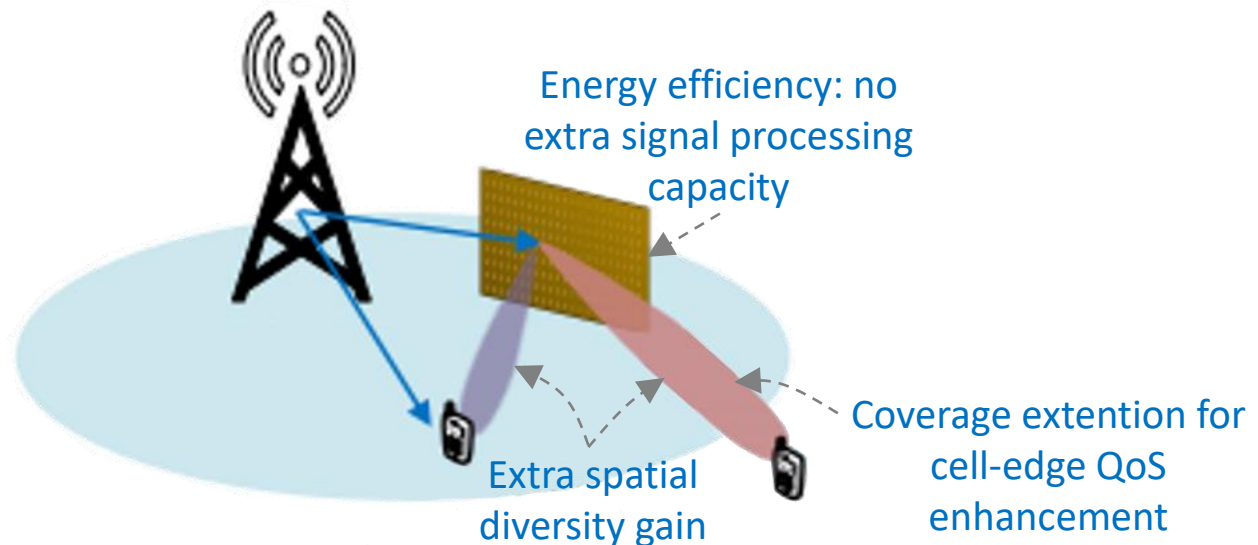
- RIS provides extra spatial diversity gain

## Coverage extension

- RIS as a passive relay can assist APs to serve cell-edge users

## Energy efficiency improvement

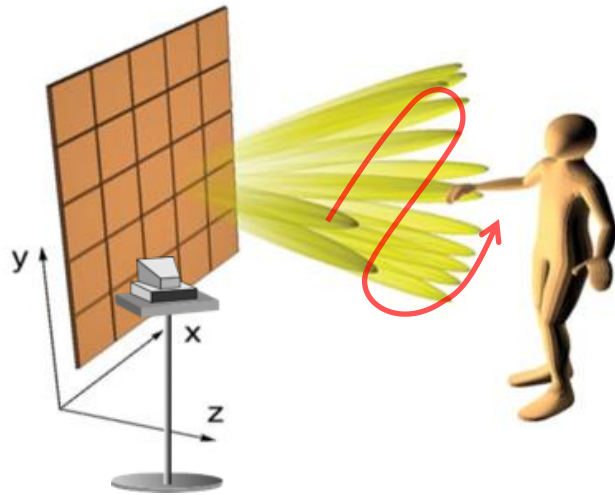
- RIS does not need extra energy-consuming hardware to be deployed



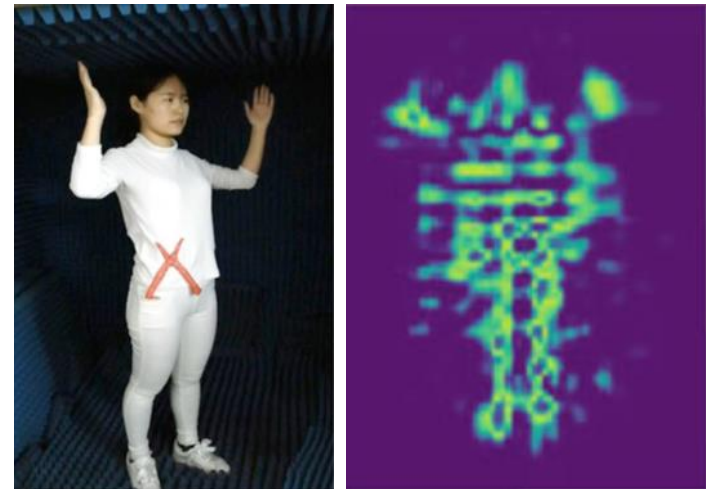
# Applications: Radio Frequency Sensing

## Indoor Localization and Recognition

- Enhance remote RF sensing by **customize radio environments**.
- Enable **high accuracy** indoor human and object localization and recognition

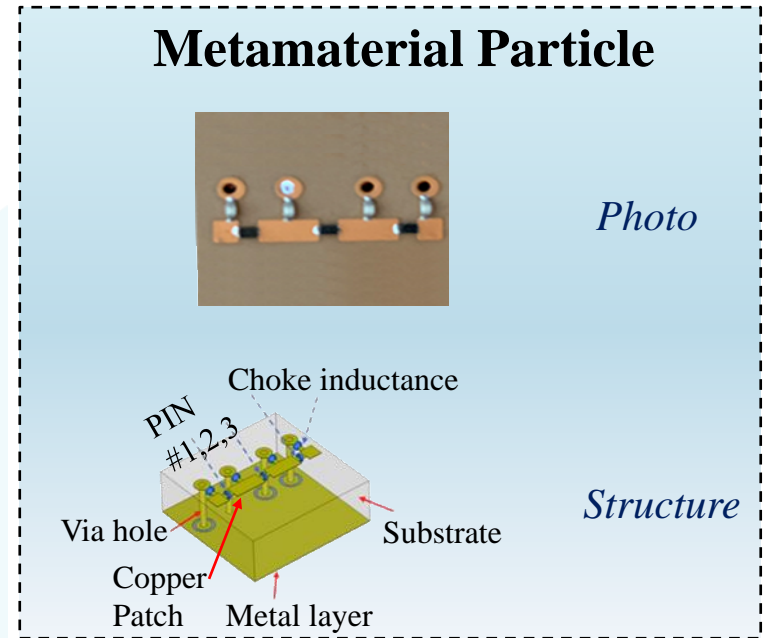
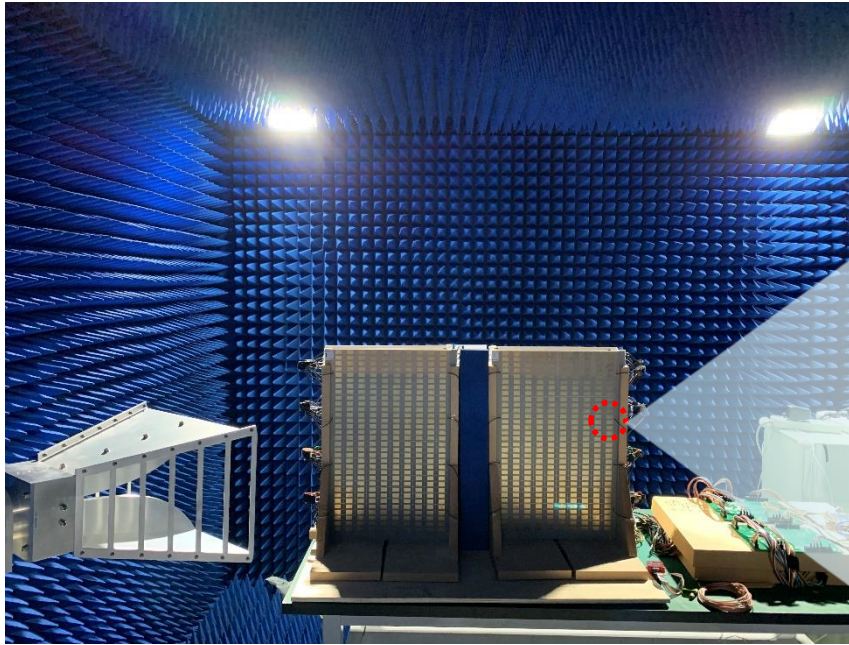


Customize signal beams for scanning human location



Customized radio environment for sensing human posture

# Prototype of Metasurface



- **Size of metasurface:**  $45 \times 57 \times 0.71 \text{ cm}^3$ , total 640 metamaterial particles
- **Size of each metamaterial particle:**  $2.87 \times 1.42 \text{ cm}^2$
- **Total number of possible phase shifts:** 4
  - 2 of them are used, and have phase shifts with interval  $\pi$
- **Working frequency:** 3.6 GHz

\* Photo shows the actual metasurface prototype used as the testbed in PKU lab.

# RIS vs. Existing Technologies

Technology	Operating mechanism	Duplex	No. of transmit RF chains needed	Hardware cost	Energy consumption
RIS	Passive/Active, reflection	Full	0	Low	Low
Massive MIMO	Active, transmission/reception	Half/full	N	Very high	Very high
Relay	Active, reception and transmission	Half/full	N	High	High
Backscatter	Passive, reflection	Full	0	Very low	Very low

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- RIS-aided RF 3D Sensing
- RIS-aided Indoor Localization

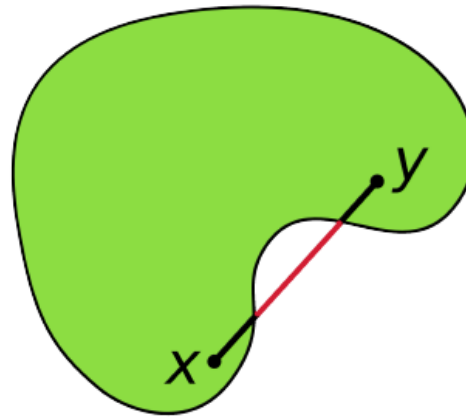
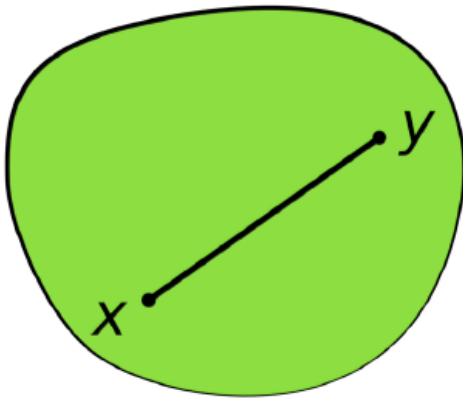
# Optimization Theory

- Convex Set and Convex Functions
- Gradient Descent and Newton's Method
- Duality and KKT Condition

# Convex Set

- A set  $S \subseteq \mathbb{R}^n$  is **convex** if for any  $x, y \in S$  and any  $\lambda \in [0, 1]$ , we have

$$\lambda x + (1 - \lambda)y \in S$$



- There are **convex sets** and **non-convex sets**
- **Note:** There is no such thing as a “concave set”

# Convex Function

- Suppose  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  satisfies

$$f(\lambda \mathbf{a} + (1 - \lambda)\mathbf{b}) \leq \lambda f(\mathbf{a}) + (1 - \lambda)f(\mathbf{b}), \quad \forall \lambda \in [0, 1], \mathbf{a}, \mathbf{b} \in \mathbb{R}^n$$

then  $f$  is called a convex function. [or  $-f$  is called a concave function]

- Intuitively, a convex function “holds water”

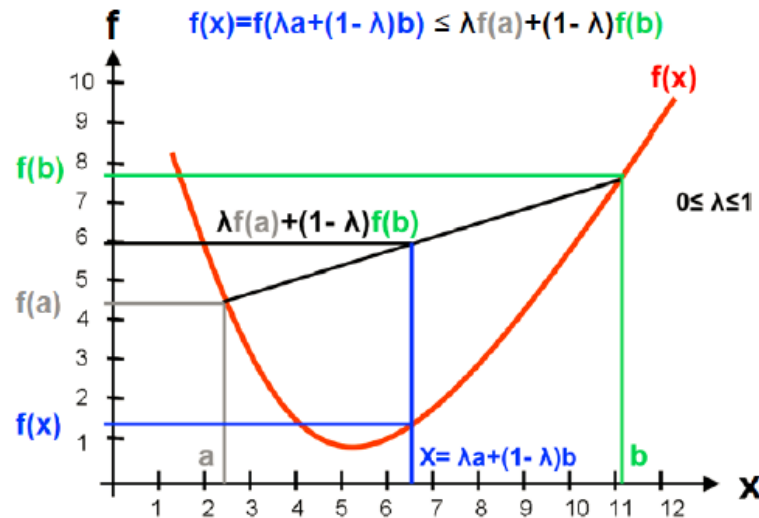


Figure: Illustration of a Convex Set [Moura 14]

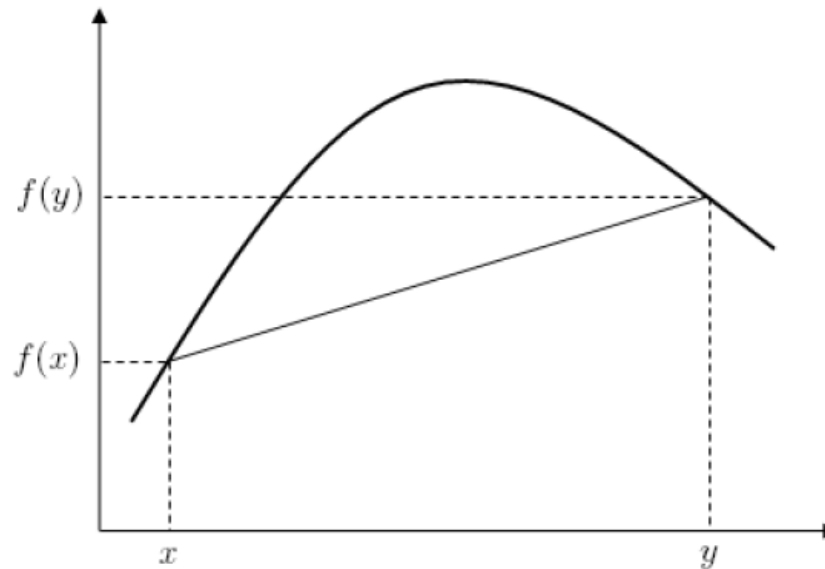


# Concave Function

- A function  $f : \mathbb{R}^n \mapsto \mathbb{R}$  is called *concave* if for all  $x, y \in \mathbb{R}^K$  and for all  $\lambda \in [0, 1]$ , we have

$$f[\lambda x + (1 - \lambda)y] \geq \lambda f(x) + (1 - \lambda)f(y).$$

- **Question:** A linear function is convex or concave function?



# Convex Optimization

$$\begin{array}{ll} \text{minimize} & f(x) \\ \text{subject to} & x \in X \end{array}$$

- Here  $f$  is continuously differentiable,  $X$  is a **convex set**
- Convex set  $X$  means we allow the following types of constraints
  - 1  $g(x) \leq 0$  where  $g(x)$  is a **convex** function
  - 2  $h(x) = 0$  where  $h(x)$  is an **affine** function:  $Cx + d = 0$

Convex means local minimum = global minimum

# Algorithms to Find Optimum

- Now we have settled the question of when global min = local min
- We are then interested in finding such “global min”
- **Easiest way**: Simply solve  $\nabla f(\mathbf{x}) = 0$ !
- Suppose  $\nabla f(\mathbf{x}) = 0$  is not easy, don't know how to solve
- Then what?

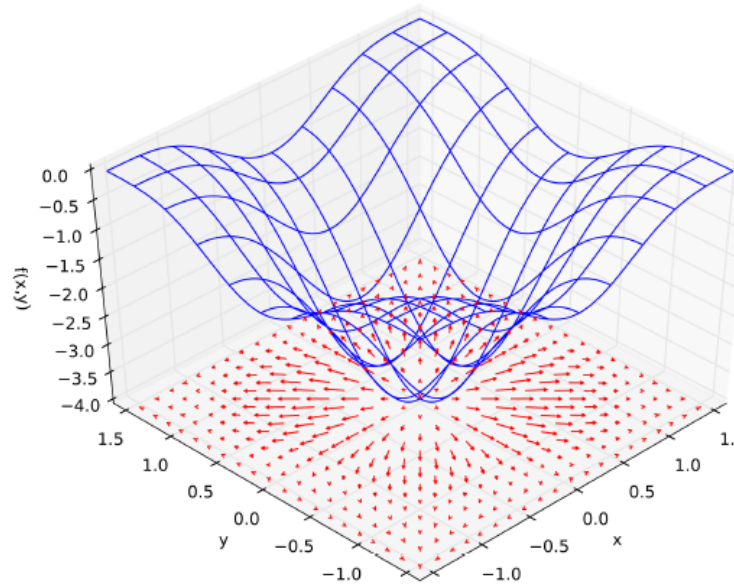


Figure: The gradients of a function (Wikipedia: Gradient)

# Gradient Descent Method

- If  $\nabla f(\mathbf{x}) = 0$ , then  $\mathbf{x}$  is a candidate solution (satisfying first-order sufficient condition); Done
- If  $\nabla f(\mathbf{x}) \neq 0$ , there is an interval  $(0, \delta)$  of stepsizes such that

$$f(\mathbf{x} - \alpha \nabla f(\mathbf{x})) < f(\mathbf{x}), \forall \alpha \in (0, \delta).$$

- Show this using [Mean Value Theorem](#) [on board]?
- More generally, if a given direction  $\mathbf{d}$  that is with obtuse angle with  $\nabla f(\mathbf{x})$

$$\langle \nabla f(\mathbf{x}), \mathbf{d} \rangle < 0$$

there is an interval  $(0, \delta)$  of stepsizes such that

$$f(\mathbf{x} + \alpha \mathbf{d}) < f(\mathbf{x}), \forall \alpha \in (0, \delta).$$

# Iterative Descent Method

$$\mathbf{x}^{r+1} = \mathbf{x}^r + \alpha_r \mathbf{d}^r, \quad r = 0, 1, \dots$$

where, if  $\nabla f(\mathbf{x}^r) \neq 0$ , the direction  $\mathbf{d}^r$  satisfies  $\nabla f(\mathbf{x}^r) \mathbf{d}^r < 0$ , and  $\alpha^r$  is a positive stepsize

- **General Case:** Gradient descent methods

$$\mathbf{x}^{r+1} = \mathbf{x}^r - \alpha_r \mathbf{D}^r \nabla f(\mathbf{x}^r), \quad r = 0, 1, \dots$$

where  $\mathbf{D}^r$  is a positive definite matrix

- **Special case I:** Steepest descent

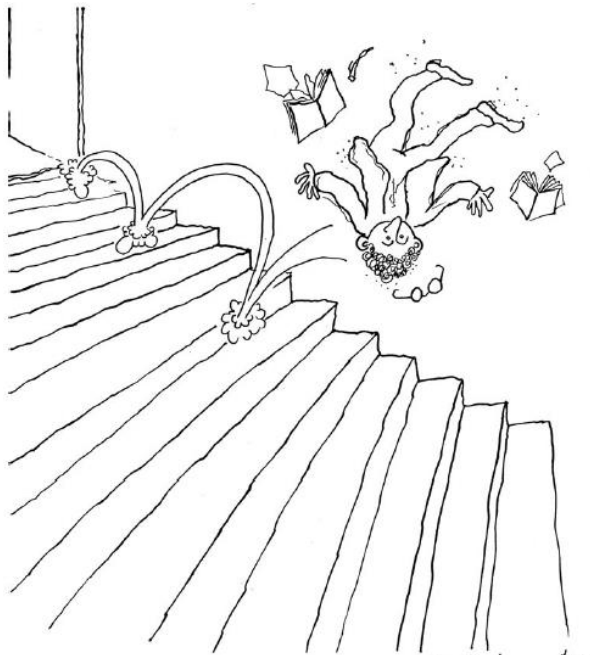
$$\mathbf{x}^{r+1} = \mathbf{x}^r - \alpha_r \nabla f(\mathbf{x}^r), \quad r = 0, 1, \dots$$

- **Special case II:** Newton's method

$$\mathbf{x}^{r+1} = \mathbf{x}^r - \alpha_r (\nabla^2 f(\mathbf{x}^r))^{-1} \nabla f(\mathbf{x}^r), \quad r = 0, 1, \dots$$

# Shortcoming of Gradient Method

However, in practice steepest descent may have slow convergence



*Just after learning the "Steepest Descent" method  
in optimization class...*

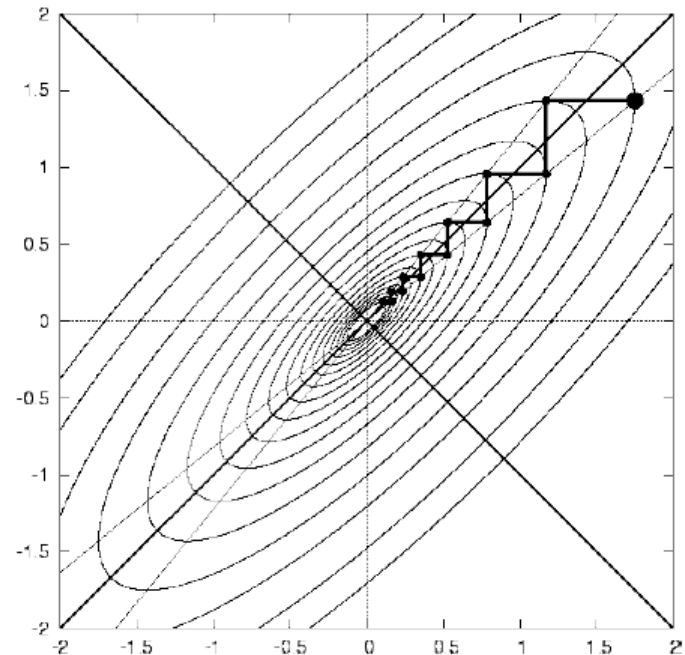


Figure: The Steepest Descent in Practice (Komarix.org)

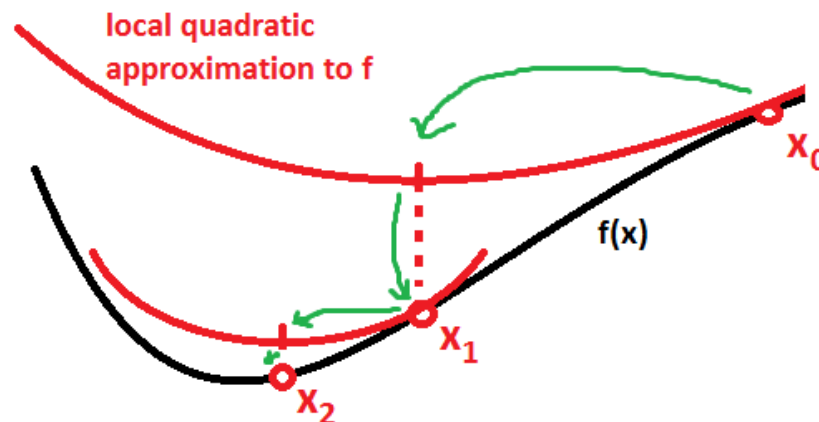
Figure: The Steepest Descent (ERASIP: DSPHumour)

# Newton's Method

- Newton's method: generally fast convergence
  - ▶ Basically it treats the objective (locally) as a quadratic problem around  $\mathbf{x}^r$

$$f(\mathbf{x}) \approx f(\mathbf{x}^r) + \langle \nabla f(\mathbf{x}^r), \mathbf{x} - \mathbf{x}^r \rangle + \frac{1}{2}(\mathbf{x} - \mathbf{x}^r)^T \nabla^2 f(\mathbf{x}^r)(\mathbf{x} - \mathbf{x}^r)$$

- ▶ **Question:** how many iterations does it take for Newton method to minimize a quadratic function  $f$ ?
- ▶ **Caution:** very difficult to make it numerically stable, needs more information than the steepest descent method



# Lagrangian Multiplier

$$\begin{aligned} &\text{minimize} && f(x) \\ &\text{subject to} && h_i(x) = 0, \quad i = 1, \dots, m \\ & && g_j(x) \leq 0, \quad j = 1, \dots, n \end{aligned}$$

- **Reminder:** The problem is called **convex problem** if
  - 1  $f(x)$  is a convex function
  - 2  $h_i(x)$  is an affine function, i.e.,  $h_i(x) = Ax + b$
  - 3  $g_j(x)$  is a convex function
- The **Lagrangian** can be formed using the Lagrangian multipliers  $\lambda_i \geq 0$  and  $\nu_i \in \mathbb{R}$

$$L(x, \lambda, \nu) = f(x) + \sum_{j=1}^n \lambda_j g_j(x) + \sum_{i=1}^m \nu_i h_i(x)$$



# Duality

- The Lagrangian dual function

$$L^*(\lambda, \nu) = \inf_{x \in X} L(x, \lambda, \nu) = \inf_{x \in X} f(x) + \sum_{j=1}^n \lambda_j g_j(x) + \sum_{i=1}^m \nu_i h_i(x)$$

- The Dual Problem

$$\max_{\lambda, \nu} L^*(\lambda, \nu), \quad \text{s.t. } \lambda \geq 0$$

- $\lambda_i$  and  $\nu_i$ 's can be viewed as “prices” for violating the constraints
- Let  $f^*$  be the optimal value of  $f(x)$
- The Lagrangian dual  $L^*$  is
  - 1 A concave function: even when the original problem is not convex
  - 2 A lower bound: for  $\lambda \geq 0$ ,  $L^*(\lambda, \nu) \leq f^*$

# Duality

- Let  $d^*$  be the **optimal objective of the dual**
- Weak duality:  $d^* \leq f^*$ 
  - 1 Always true
  - 2 Non-trivial lower bound for hard problems
  - 3 Useful in approximation algorithms
- Strong duality:  $d^* = f^*$ 
  - 1 Does not hold in general
  - 2 If holds, sufficient to solve the dual
  - 3 How to check if it holds?
- Constraint qualification
  - 1 Normally true for **convex problems**
  - 2 True if the problem is convex; And it is **strictly feasible**, i.e. there **exists** a  $x \in X$  such that
$$h_i(x) = 0, \quad g_j(x) < 0$$
  - 3 The above condition is known as the **Slater's condition**

# KKT Condition: When to Stop?

$$\begin{aligned} & \text{minimize} && f(x) \\ & \text{subject to} && h_i(x) = 0, \quad i = 1, \dots, m && (1) \\ & && g_j(x) \leq 0, \quad j = 1, \dots, n && (2) \end{aligned}$$

Any optimal and dual pairs  $\tilde{x}$  and  $(\tilde{\lambda}, \tilde{\nu})$  must satisfy



Albert  
Tucker

$$\begin{aligned} \nabla f(\tilde{x}) + \sum_{j=1}^n \tilde{\lambda}_j \nabla g_j(\tilde{x}) + \sum_{i=1}^m \tilde{\nu}_i \nabla h_i(\tilde{x}) &= 0_{K \times 1} \\ g_j(\tilde{x}) \leq 0, \forall j = 1, \dots, n, & \quad (\text{primal feasibility}) \\ h_i(\tilde{x}) = 0, \forall i = 1, \dots, m, & \quad (\text{primal feasibility}) \\ \tilde{\lambda}_j \geq 0, \forall j = 1, \dots, n, & \quad (\text{dual feasibility}) \\ g_j(\tilde{x}) \times \tilde{\lambda}_j = 0, \forall j & \quad (\text{complementarity}). \end{aligned}$$



Harold  
Kuhn

# Barrier Function

reformulation of (1) via indicator function:

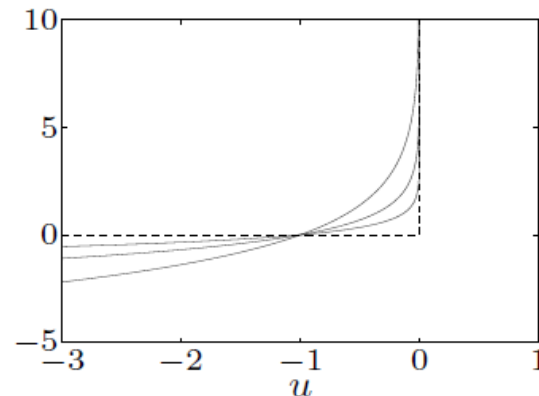
$$\begin{aligned} & \text{minimize} && f_0(x) + \sum_{i=1}^m I_-(f_i(x)) \\ & \text{subject to} && Ax = b \end{aligned}$$

where  $I_-(u) = 0$  if  $u \leq 0$ ,  $I_-(u) = \infty$  otherwise (indicator function of  $\mathbf{R}_-$ )

approximation via logarithmic barrier

$$\begin{aligned} & \text{minimize} && f_0(x) - (1/t) \sum_{i=1}^m \log(-f_i(x)) \\ & \text{subject to} && Ax = b \end{aligned}$$

- an equality constrained problem
- for  $t > 0$ ,  $-(1/t) \log(-u)$  is a smooth approximation of  $I_-$
- approximation improves as  $t \rightarrow \infty$



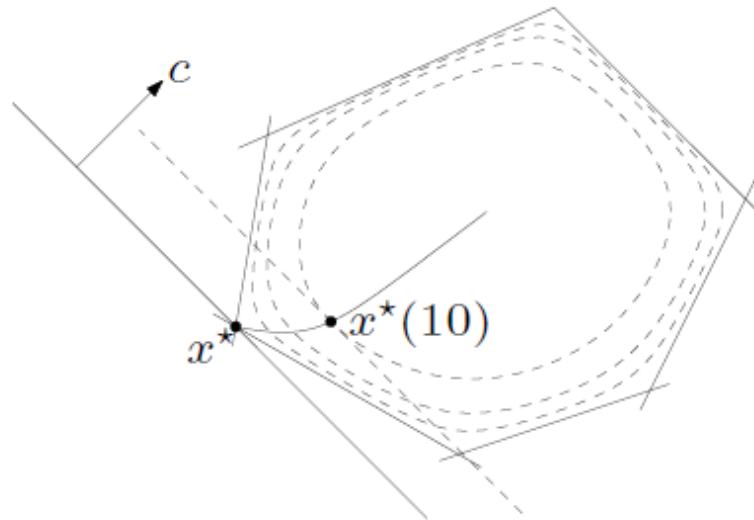
# Interior Point Method

---

**given** strictly feasible  $x$ ,  $t := t^{(0)} > 0$ ,  $\mu > 1$ , tolerance  $\epsilon > 0$ .

**repeat**

1. *Centering step.* Compute  $x^*(t)$  by minimizing  $tf_0 + \phi$ , subject to  $Ax = b$ .
  2. *Update.*  $x := x^*(t)$ .
  3. *Stopping criterion.* **quit** if  $m/t < \epsilon$ .
  4. *Increase  $t$ .*  $t := \mu t$ .
- 



# Learning Methods

- Classical Machine Learning
- Deep Learning
- Reinforcement Learning

# Classical Machine Learning

“Computers: learn without being explicitly programmed”

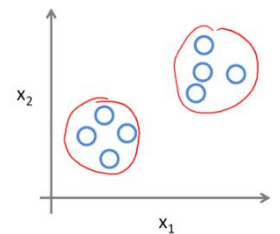
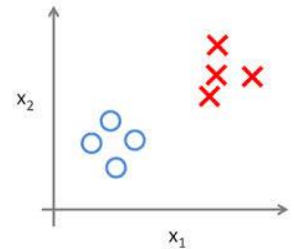
- Types:

- **Supervised Learning:**

- Example inputs (features) and their desired outputs (labels)
    - Goal: learn a general rule that maps inputs to outputs
    - SVM, neural networks, etc.

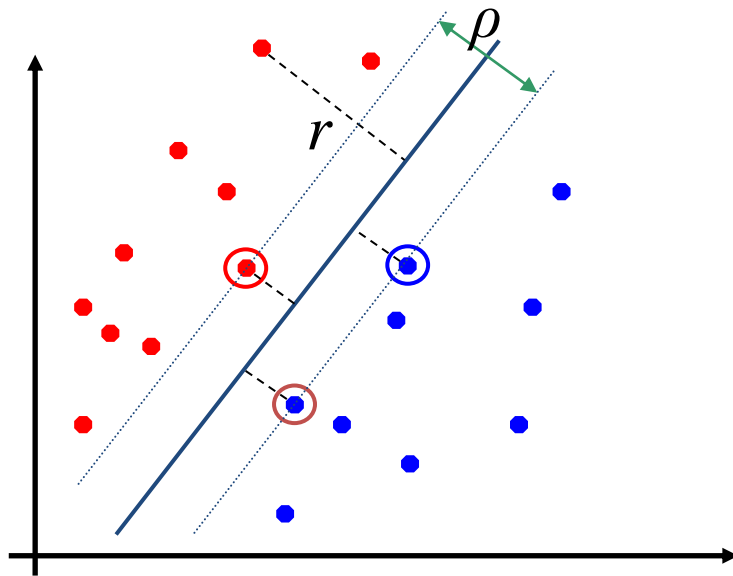
- **Unsupervised Learning:**

- No labels
    - Find structure in its input
    - Goal: discover hidden patterns in data
    - Clustering, K-means, etc.



# Supervised Learning: SVM

- Distance from sample  $x_i$  to the separator:  $r$
- Support vectors: samples closest to the hyperplane
- Margin  $\rho$ : the distance between support vectors
- Objective: maximize the margin  $\rho$



$$r = \frac{y_i(w^T x_i + b)}{|w|} = \frac{1}{|w|}$$

$$\rho = \frac{2}{|w|}$$

$$y = -1: w^T x_i + b \leq -\frac{\rho}{2}$$

$$y = 1: w^T x_i + b \geq \frac{\rho}{2}$$

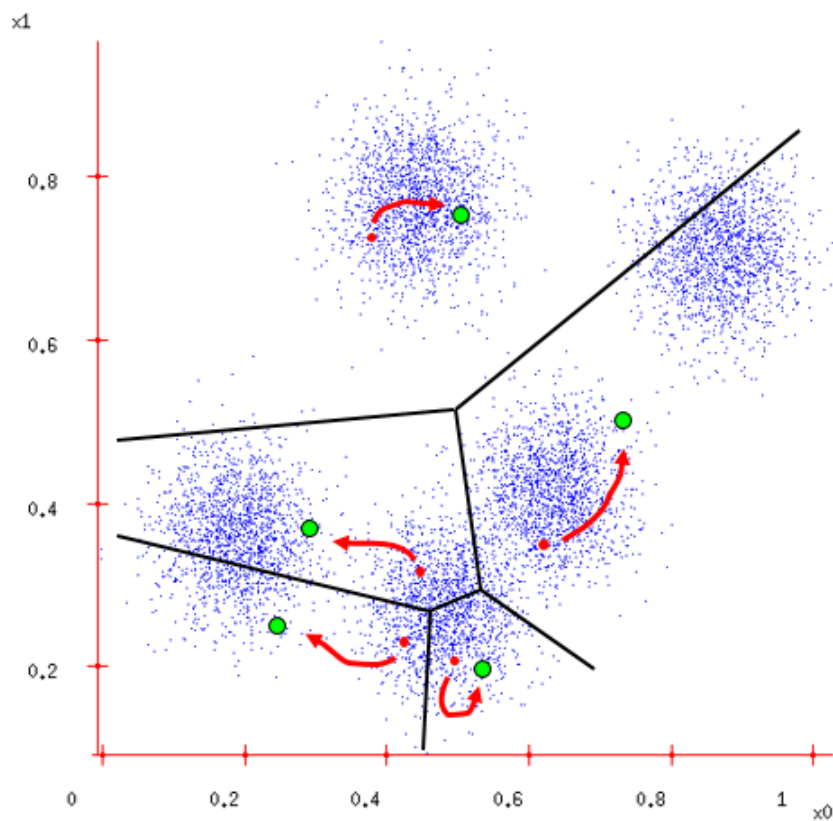


# Supervised Learning: Applications

- The best performers for a number of classification tasks ranging from text to genomic data.
- Complex data types beyond feature vectors (e.g. graphs, sequences, relational data) by designing kernel functions for such data.
- Extend to a number of tasks such as regression, principal component analysis, etc.

# Unsupervised Learning: K-Means

- Ask user how many clusters they'd like. (e.g.  $k=5$ )
- Randomly guess  $k$  cluster center locations
- Each data point: find out which center it's closest to
- Each center: find the centroid of the points it owns
- Change center
- Repeat until terminated



# Unsupervised Learning: Applications

- Data mining
- Acoustic data in speech understanding to convert waveforms into one of  $k$  categories (known as Vector Quantization or Image Segmentation)
- Also used for choosing color palettes on old fashioned graphical display devices and Image Quantization

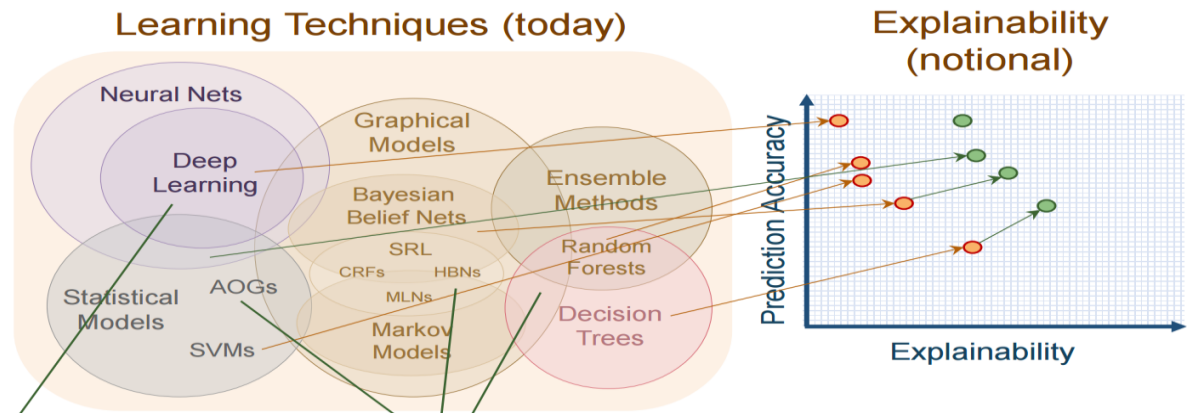
# Deep Learning: Motivations

- Classic Methods

- Do not have a lot of data, or
- Training data have categorical features
- A more explainable model
- A high run-time speed

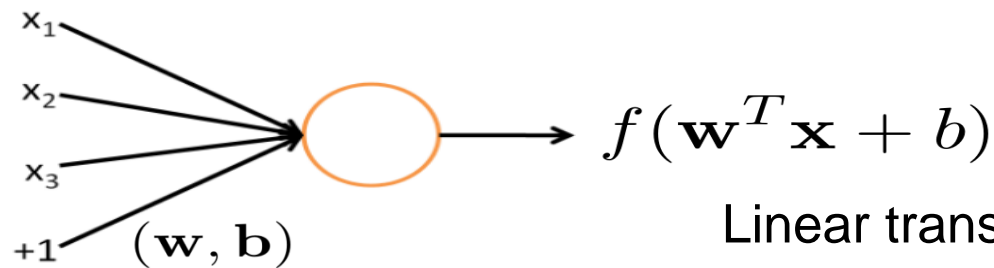
- Deep Learning

- A lot of training data of the same or related domain
- Improve Domain Adaptation
- Appropriate scaling and normalization have to be done
- Much slower

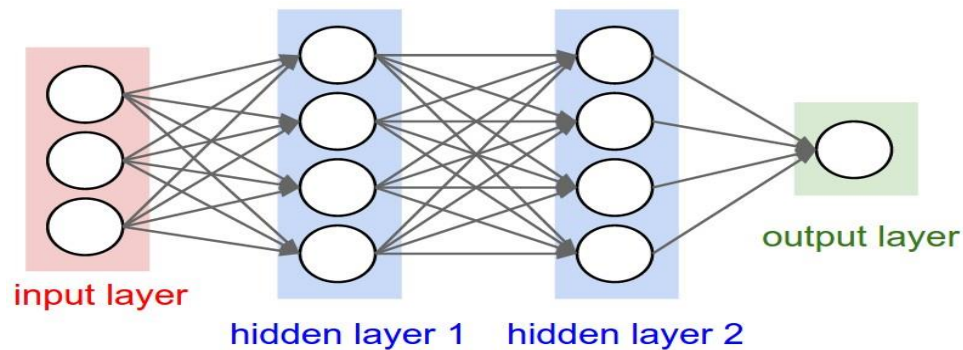


# Deep Learning: Basic Idea

- Add Hidden Layers in Neural Networks



Linear transformation followed by non-linear rectification

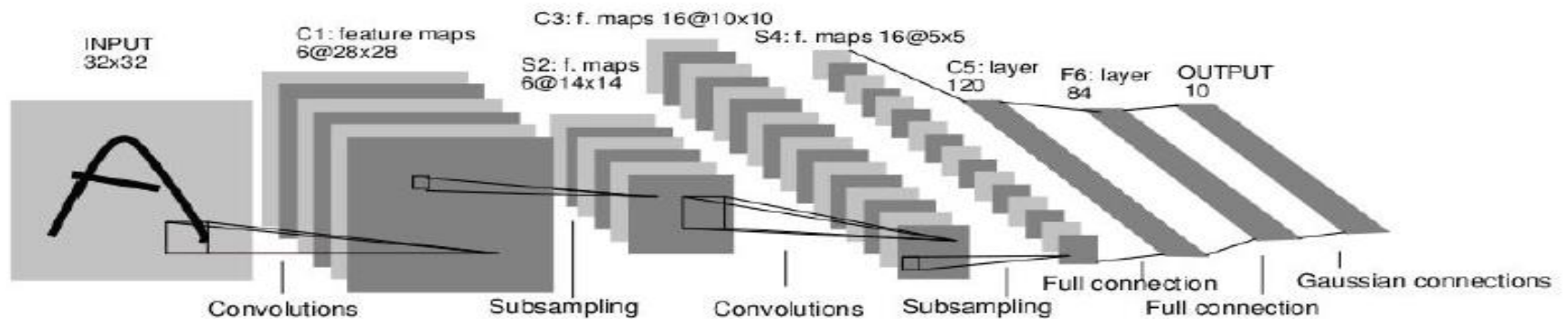
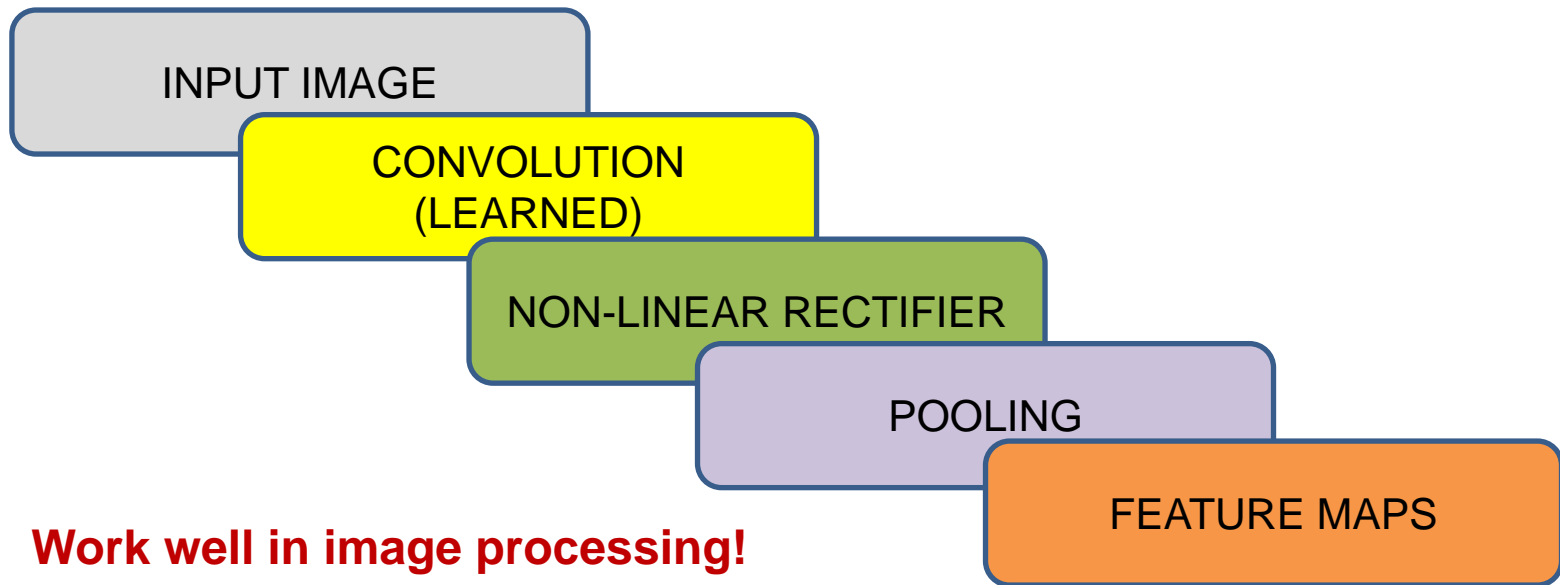


- More parameters
- More non-linear parts

# Typical Deep Neural Networks

- Convolutional Neural Networks (CNNs)
- Recurrent Neural Networks (RNNs)
- Deep Belief Networks

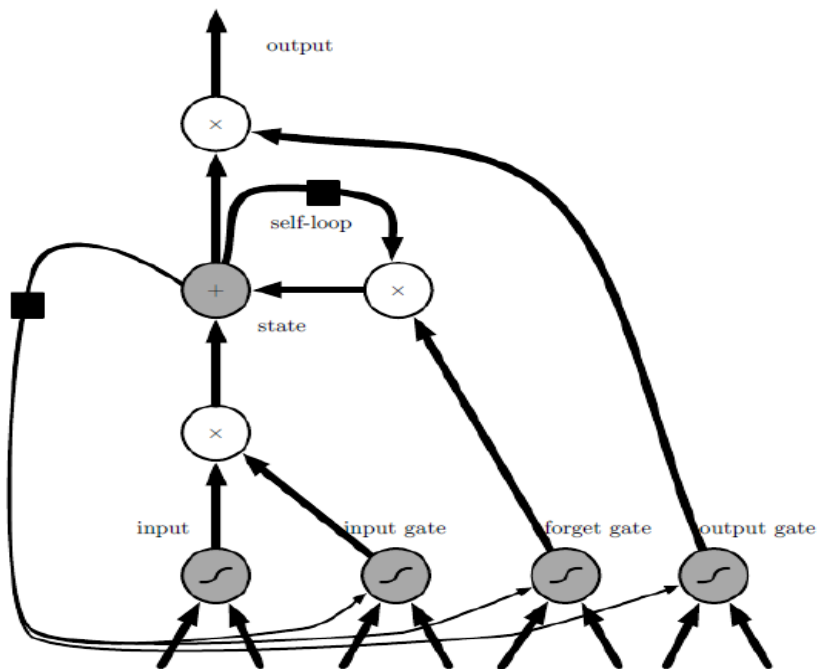
# Convolutional Neural Networks (CNNs)



[4] LeCun, Yann. "LeNet-5, convolutional neural networks". Retrieved Nov. 2013.

# Recurrent Neural Networks (RNNs)

- Produce an output at each time step and have recurrent connections between hidden units
  - Long Short-Term Memory

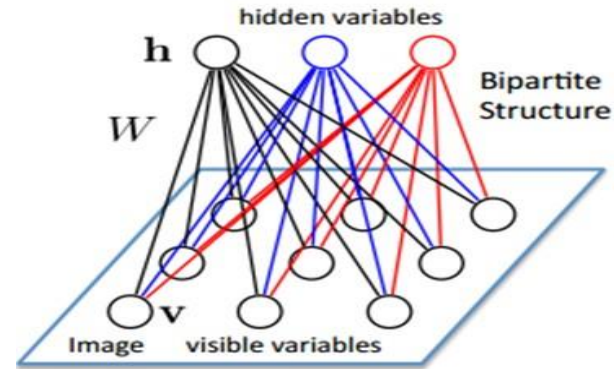
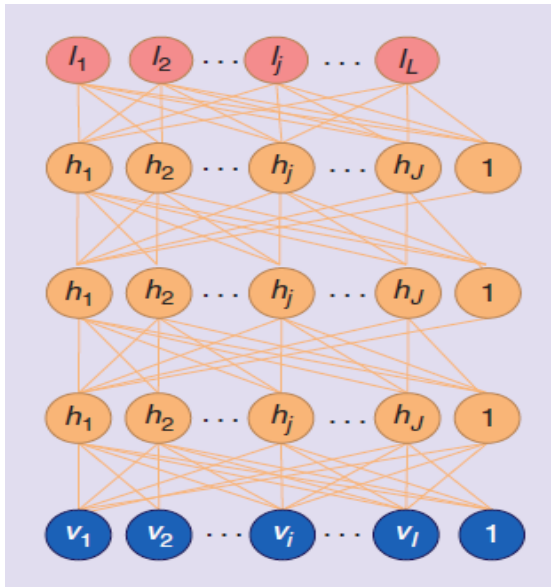


- Unconstrained handwriting recognition (Graves et al., 2009),
- Speech recognition (Graves et al., 2013; Graves and Jaitly, 2014)
- Handwriting generation (Graves, 2013),
- Machine translation (Sutskever et al., 2014)
- Image captioning (Kiros et al., 2014; Vinyals et al., 2014; Xu et al., 2015)
- Parsing (Vinyals et al., 2014a).



# Deep Belief Networks

- Each link associates with a probability
- Parametric



The energy of the joint configuration:

$$E(\mathbf{v}, \mathbf{h}; \theta) = - \sum_{ij} W_{ij} v_i h_j - \sum_i b_i v_i - \sum_j a_j h_j$$

$\theta = \{W, a, b\}$  model parameters.

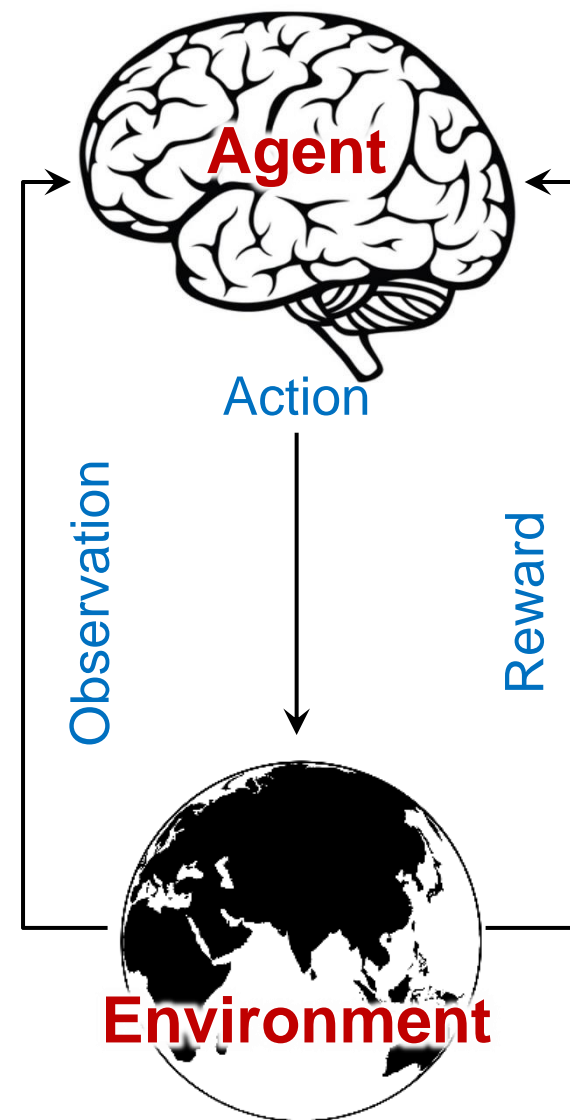
- Applied in clustering

# Comparison

	Similarities	Differences
<b>Convolutional Neural Networks</b>	<ol style="list-style-type: none"><li>1. Multiple Layers</li><li>2. Use Back-propagation Algorithm for training</li><li>3. Can be combined together to create more powerful networks</li></ol>	<ol style="list-style-type: none"><li>1. More suitable for data with grid structures</li><li>2. Much fewer parameters</li><li>3. Very efficient training with GPUs</li></ol>
<b>Recurrent Networks</b>		<ol style="list-style-type: none"><li>1. Having memory of past (suitable for tasks like speech recognition)</li><li>2. Not able to take big input such as images or videos</li></ol>
<b>Deep Belief Networks</b>		<ol style="list-style-type: none"><li>1. Generative model (can generate realistic looking data after initializing at random variable)</li><li>2. Used much less due to inefficiency</li></ol>

# Reinforcement Learning

- **Agent** — An intelligent individual
- **Environment** — Changes with the agent's action, then provides reward
- The agent observes the environment, takes action, and gets reward iteratively
- **Target of the agent** — To maximize the total reward in the long run
- In case of full observation:
  - System states can be modelled as **Markov Decision Process (MDP)**



# Markov Decision Process

- A Markov decision process further includes action in the Markov reward process, written as a tuple  $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma \rangle$

- $\mathcal{S}$  is a **finite set of the states** that have Markov property:

$$\mathbb{P}[S_{t+1} | S_t] = \mathbb{P}[S_{t+1} | S_1, \dots, S_t]$$

- Any finite set of discrete states  $\xrightarrow{\text{can be transformed}}$  Markov states

- $\mathcal{A}$  is a **finite set of the actions**, from which the agent can choose to perform at each current state

- $\mathcal{P}$  is the **state transition probability matrix**, defined as the probability of state transition based on a given action:

$$\mathcal{P}_{ss'}^a = \mathbb{P}[S_{t+1} = s' | S_t = s, A_t = a]$$

# Markov Decision Process

- A Markov decision process further includes action in the Markov reward process, written as a tuple  $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma \rangle$
- $\mathcal{R}$  is a **reward function**, showing the average reward of the next step when the current state is  $S_t$ , given as

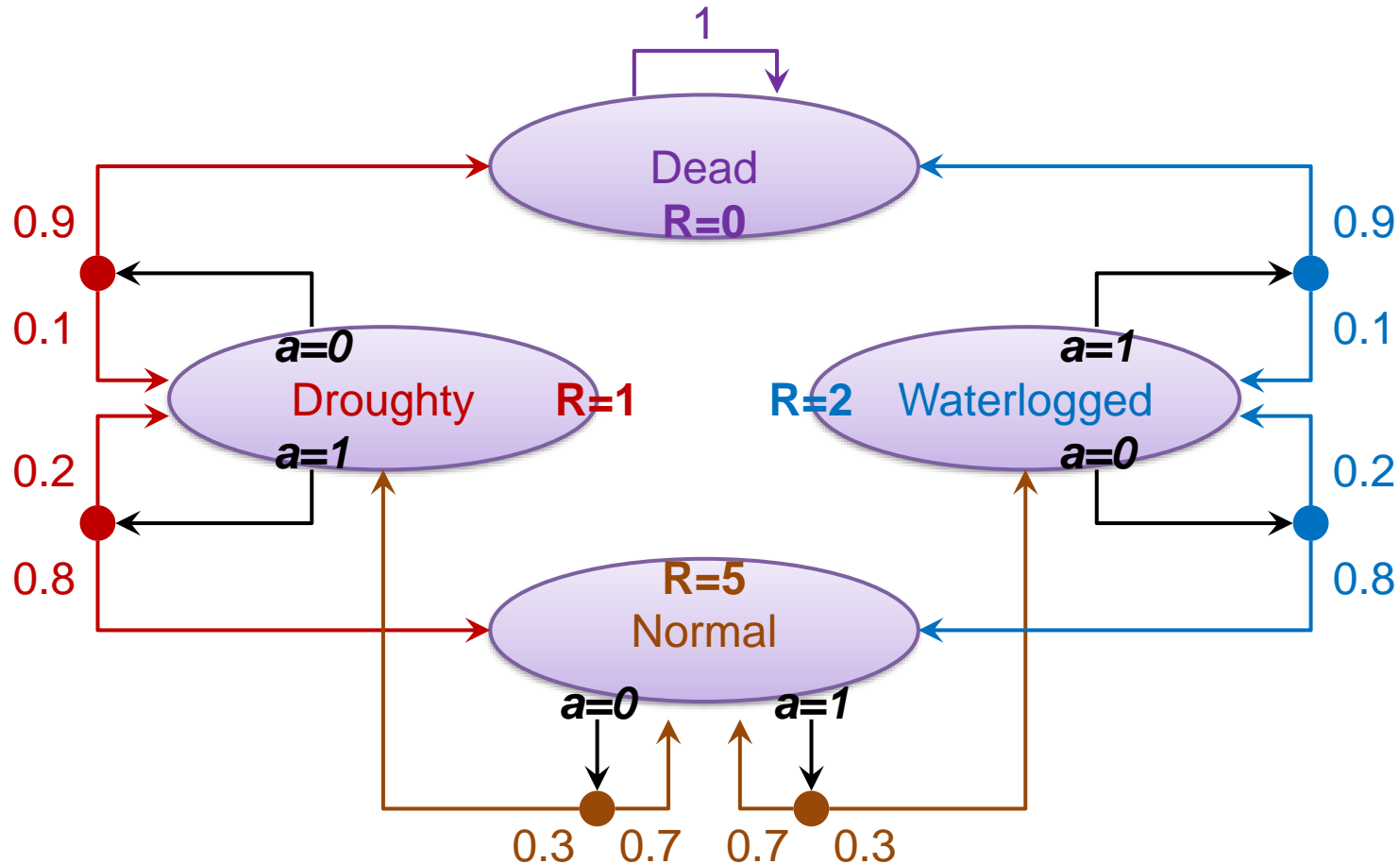
$$\mathcal{R}_s = \mathbb{E} [R_{t+1} \mid S_t = s]$$

- $\gamma$  is a **discount factor**, which is used to weaken the reward of future, given by  $\gamma \in [0, 1]$ , avoiding infinite returns in cyclic state transitions
- Denote **accumulative future reward** as:

$$G_t = R_{t+1} + \gamma R_{t+2} + \dots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$$

# Markov Decision Process: Example

- Cultivating the flower by deciding whether to water it ( $a=1$  for watering and  $a=0$  for non-watering)



# Policy and Value Function

- **Policy** is the agent's behavior
- It is a *map* from **state** to **action**
- **Deterministic:**  $a = \pi(s)$  **Stochastic:**  $\pi(a|s) = \mathbb{P}[A_t = a | S_t = s]$
- **Value function** is a prediction of future reward
- Used to evaluate the **goodness/badness of states**
- Defined as the average accumulative future reward from the current state based on the given policy  $\pi$ :
  - **State value function:**  $v_\pi(s) = \mathbb{E}_\pi [G_t | S_t = s]$
  - **Action value function:**  $q_\pi(s, a) = \mathbb{E}_\pi [G_t | S_t = s, A_t = a]$

# Optimal Policy

- What is the optimal policy?
  - A policy that leads to the highest value for any state:

$$\pi \geq \pi' \text{ if } v_{\pi}(s) \geq v_{\pi'}(s), \forall s$$

- **Theorem:** For any Markov decision process, there exists an optimal policy  $\pi_*$  that is **better than / equal to** any other policy:

$$\pi_* \geq \pi, \forall \pi$$

- There is always a **deterministic optimal policy** for any MDP, given as

$$\pi_*(a|s) = \begin{cases} 1 & \text{if } a = \operatorname{argmax}_{a \in \mathcal{A}} q_*(s, a) \\ 0 & \text{otherwise} \end{cases}$$

- Non-linear, no closed solution, many iterative methods



# Q-Learning

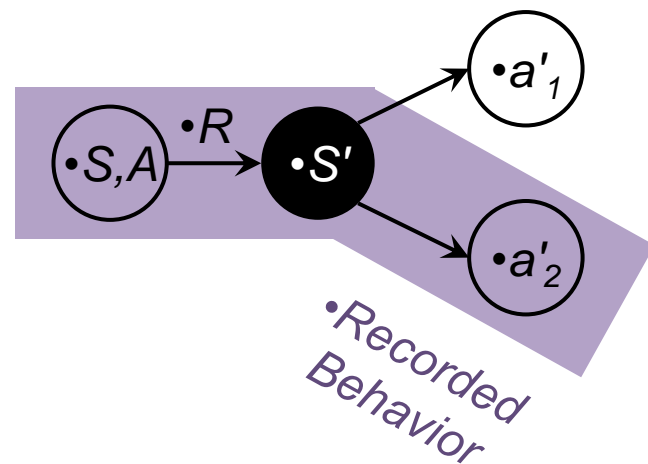
## Off-policy learning

- Experience from **behavior**  $\mu(a|s)$
- E.g., learning from existing chess movement records

- A slightly different update function

$$Q(S, A) \leftarrow Q(S, A) + \alpha \left( R + \gamma \max_{a'} Q(S', a') - Q(S, A) \right)$$

- Use the best successor action instead of the action from the behavior to update the current  $Q(S, A)$



# Table of Contents

## 1. Background

- 6G Communications and Requirements
- RIS Basics and Potential Applications

## 2. Mathematical Tools

- Optimization Theory
- Machine Learning

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- Size Effect
- Orientation and Localization
- RIS aided Multi-User Communications
- Intelligent Omni-Surface

## 4. RIS-aided RF Sensing

- RIS-aided Posture Recognition
- RIS-aided RF 3D Sensing
- RIS-aided Indoor Localization

# Goals and Challenges in RIS-aided Cellular Communication

## Goals

- Higher energy efficiency
- Higher capacity / Lower interference
- Larger coverage

## Challenges

- How to design the number of phase shifts?
- How to deploy the RIS (orientation and location)?
- How does the size of RIS influence the performance?
- How to design the RIS configuration (phase shift)?
- How to coordinate multi-user access?

# Case Study I: Limited Phase Shifts Effect

## RIS assisted Communications with Limited Phase Shifts: How Many Phase Shifts Are Enough?

H. Zhang, et al, "Reconfigurable Intelligent Surfaces assisted Communications with Limited Phase Shifts: How Many Phase Shifts Are Enough?" IEEE Transactions on Vehicle Technology, vol. 69, no. 4, pp. 4498-4502, Apr. 2020.

# Motivations and Contributions

## Problems

- Lack of the **performance limit analysis** of RIS-aided cellular communication.
- **Most works assume continuous phase shifts**, which are hard to be implemented in practice.
- **It is worthwhile to study the impact of the limited phase shifts on the achievable data rate.**

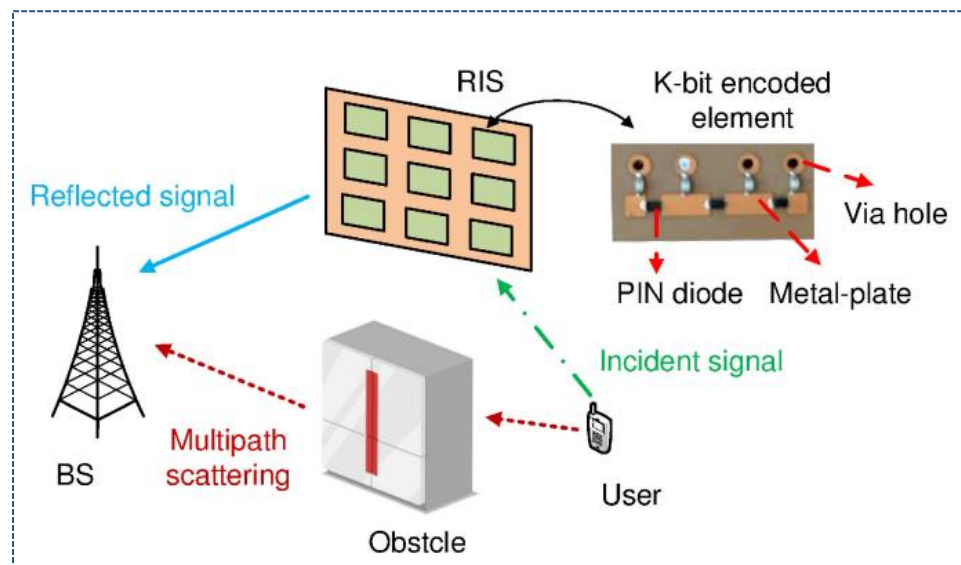
## Contributions

- We provide an analysis on the **achievable data rate** with **continuous phase shifts** of the RIS, to evaluate the performance limits of the RIS assisted communications.
- We discuss **how the limited phase shifts influence the data rate** based on the derived achievable data rate expression.

# System Model

## System Description

- Single cell uplink network
- LoS between the BS and the user is blocked
- RIS to reflect user's signal to BS
- Phase shift of RIS element
  - $K$ -bit quantized, i.e.,  $2^K$  uniformly-spaced



- The uplink data rate of the user can be expressed by

$$\mathbb{E} [\log_2(1 + \gamma)] \approx \log_2 \left( 1 + \underbrace{\frac{\eta_{LoS}}{\kappa+1}}_{\text{LoS path loss}} MN + \underbrace{\frac{\xi \eta_{NLoS}}{\kappa+1}}_{\text{NLoS path loss}} \sum_{m,m',n,n'} e^{-j[\underbrace{\phi_{m,n} - \phi_{m',n'}}_{\text{Channel phases}} + \underbrace{\theta_{m,n} - \theta_{m',n'}}_{\text{Phase shifts}}]} \right)$$

- Ideally, channel phase and phase shift corresponding to each RIS element should satisfy  $\theta_{m,n}^* + \phi_{m,n} = \text{Constant}$ , to max data rate

# Analysis on Number of Phase Shifts

- Phase shifts errors

$$\delta_{m,n} = \underbrace{\theta_{m,n}^*}_{\text{Continuous}} - \underbrace{\hat{\theta}_{m,n}}_{\text{Discrete}}$$

- With  $K$  bit quantized, the errors can be bounded by

$$-\frac{2\pi}{2^{K+1}} \leq \delta_{m,n} < \frac{2\pi}{2^{K+1}}$$

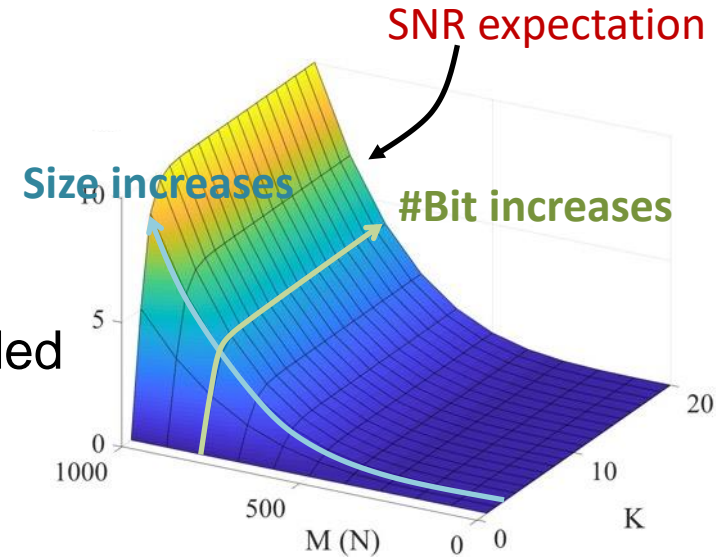
- SNR expectation with limited phase shifts

$$\mathbb{E}[\hat{\gamma}] \geq \frac{\eta_{NLoS}}{\kappa+1} MN + \frac{\kappa\eta_{LoS}}{\kappa+1} M^2 N^2 \cos^2\left(\frac{2\pi}{2^{K+1}}\right)$$

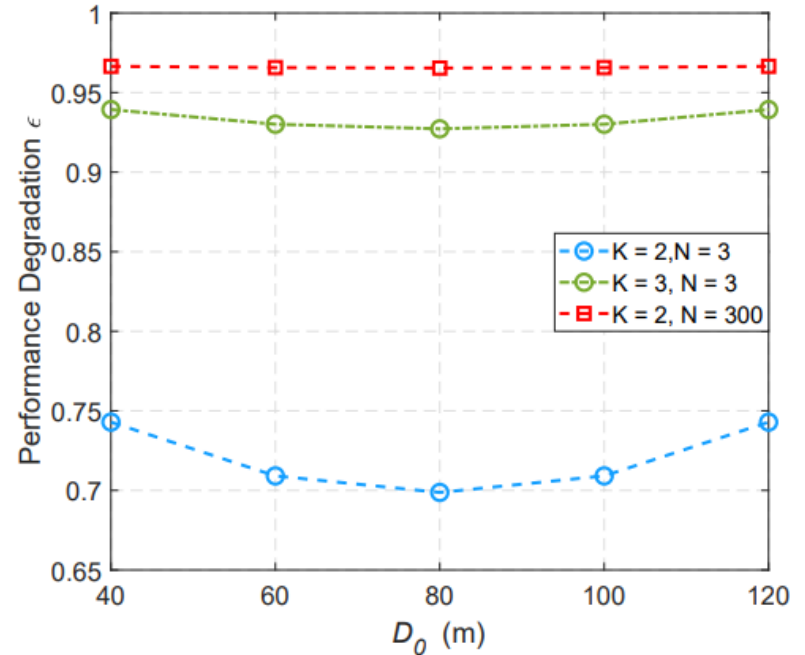
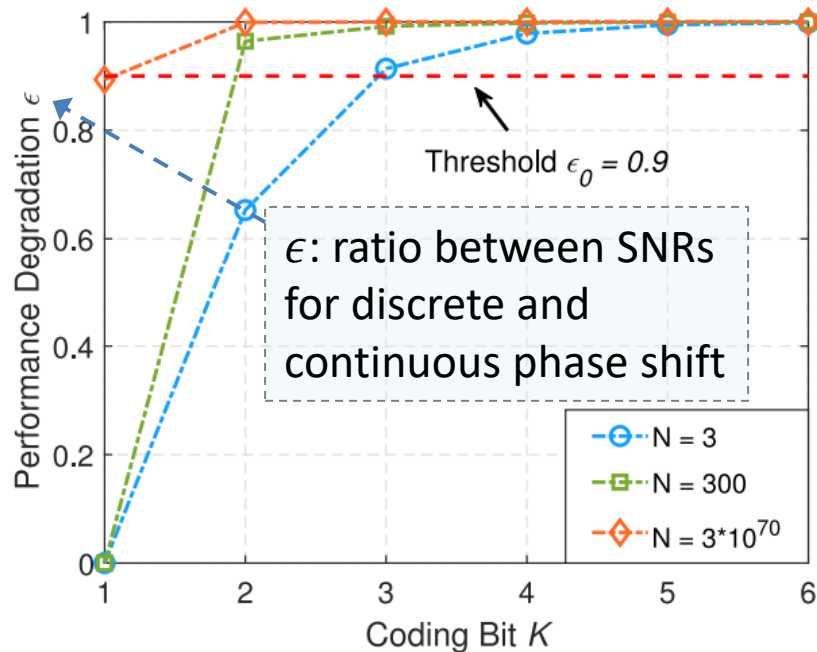
- Therefore, the expected received SNR given RIS with discrete phase shifts satisfies that

$$\mathbb{E}[\text{SNR}] \propto (\text{RIS's size})^2 \cdot \cos^2\left(\frac{2\pi}{2^{(\# \text{ Quantized bits})+1}}\right)$$

- Increase the RIS's size can help alleviate the SNR loss due to small  $K$ .



# Simulation Results



- Required quantized bits **decrease as** the number of RIS elements grows, and **1 bit** is enough when the RIS size goes to infinity
- We can easily observe that the data rate degradation will **decrease first** and **then increase** as the distance between the RIS and the BS increases given RIS size and quantized bit



# Case Study II: Size Effect

## Reconfigurable Intelligent Surface assisted Multi-user Communications: How Many Reflective Elements Do We Need?

H. Zhang et al, "Reconfigurable Intelligent Surface assisted Multi-user Communications: How Many Reflective Elements Do We Need?" IEEE Wireless Communications Letters, early access.

# Motivations and Contributions

## Problems

- Most works focus on the **phase shift optimization/analysis** in RIS assisted wireless communications
- The size of the RIS will also influence the system sum rate
- It is worthwhile to study **how many RIS reflective elements** are sufficient to provide an acceptable system sum-rate

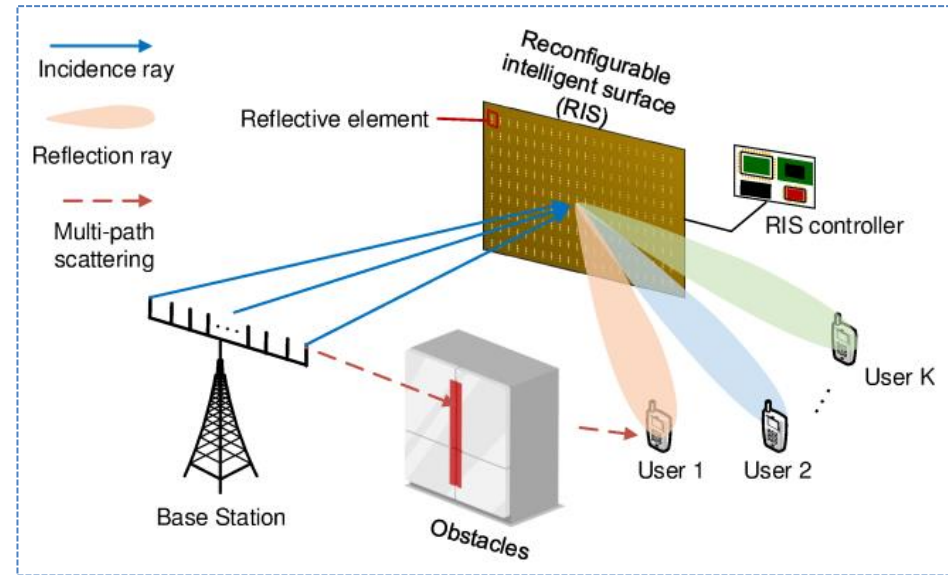
## Contributions

- We provide an **asymptotic analysis** of the system capacity for the RIS-assisted downlink multi-user MISO communications with **zero-forcing (ZF) precoding**
- We discuss **how the size of the RIS influences the data rate** based on the derived achievable data rate expression.

# System Model

## System Description

- Single cell downlink network
- LoS between the BS and users is blocked
- RIS reflects signals from the BS to users



## Data Rate Analysis

- When the number of elements is large, the channel response follows a **Gaussian distribution** (central limit theorem)
- With this assumption, the system capacity can be upper bounded by

$$C \leq \sum_k \log_2 \left( 1 + \frac{\overset{\text{Transmit power}}{P} \overset{\text{Number of RIS elements}}{\Lambda^k}}{\underset{\text{Number of users}}{K}} \bar{\beta}^k \Gamma^2 \underset{\text{Number of antennas}}{MN} \right)$$

# Analysis on Number of RIS Elements

- Minimize the number of elements with the constraint that the sum-rate can reach  $\eta$  of the system capacity bound

$$\min_N N, \quad s.t. \quad \epsilon \geq \eta.$$

Ratio of sum-rate to the system capacity bound (rate ratio)

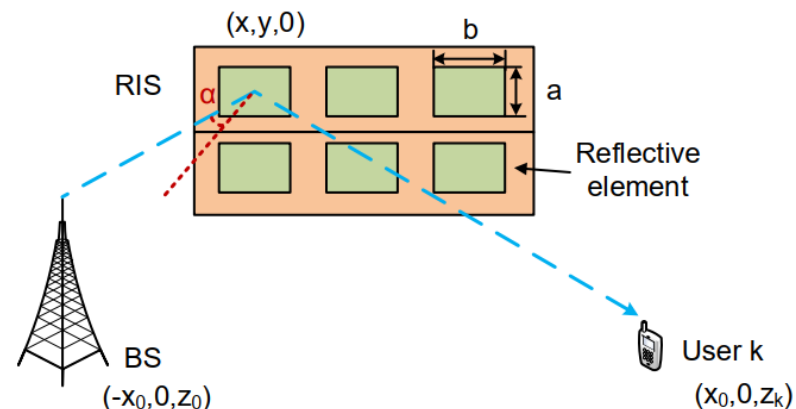
- $\epsilon$  is hard to obtain since we do not have a closed-form expression of phase shifts: use **the lower bound** of  $\epsilon$  instead
- Using Jensen's inequality, the lower bound of  $\epsilon$

$$\hat{\epsilon} = \frac{\sum_k \log_2 (1 + P\Lambda_k \Gamma^2 \bar{\beta}^k N(\mu - 1))}{\sum_k \log_2 \left( 1 + P\Lambda_k \Gamma^2 \mu \frac{2Az_0^3 \lambda^2}{5\pi^2 (z_0 + z_k)^5} \right)}$$

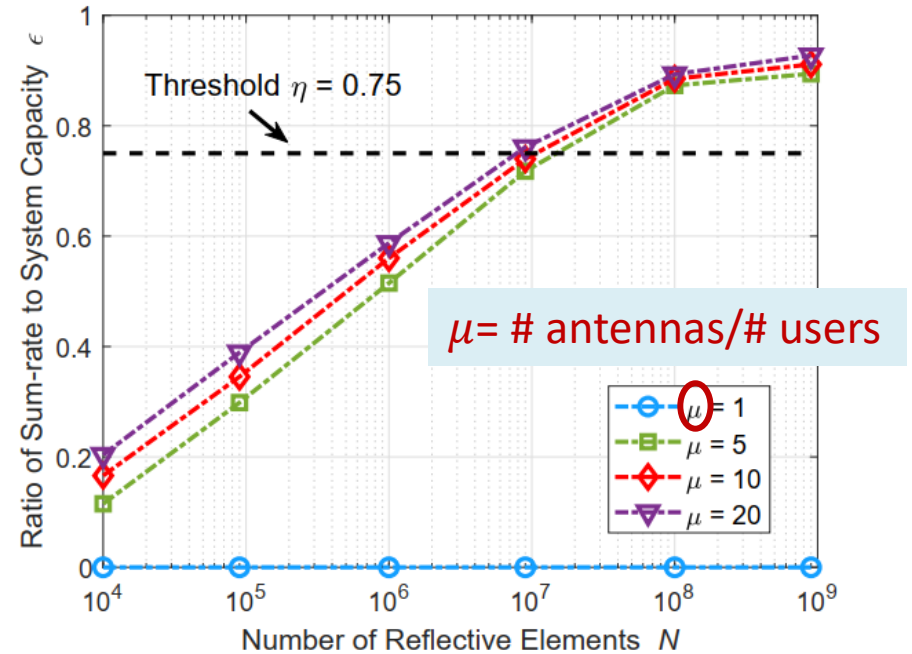
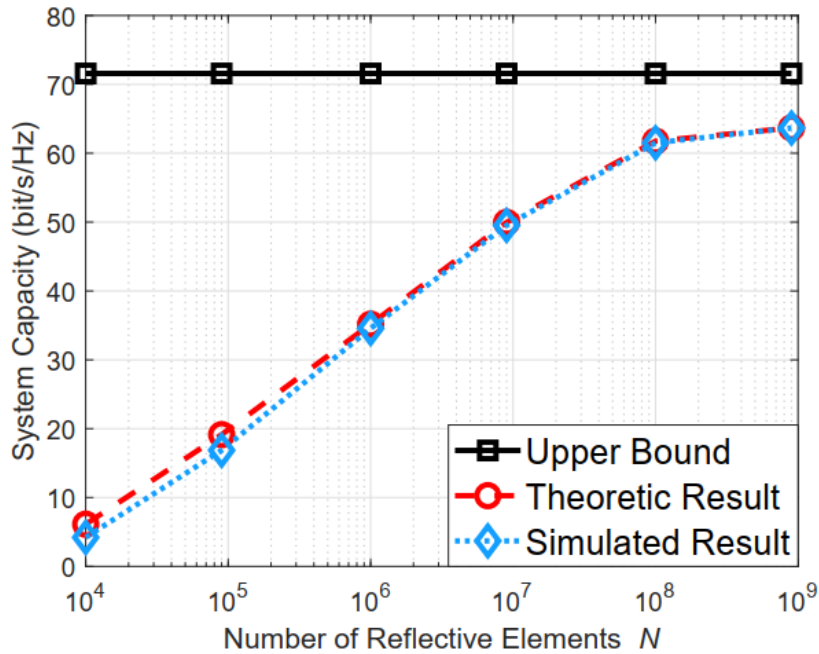
$\mu = \# \text{ BS antennas} / \# \text{ users}$   
wavelength

- The minimum number of elements

$$N \geq \left( \prod_k \frac{\left( P\Lambda_k \Gamma^2 \mu \frac{2Az_0^3 \lambda^2}{5\pi^2 (z_0 + z_k)^5} \right)^\eta}{P\Lambda_k \Gamma^2 \bar{\beta}^k (\mu - 1)} \right)^{1/K}$$



# Simulation Results



- The data rate per user will **increase first** and then become **saturated**
- **The size of the RIS** can be reduced with **more antennas at the BS**.
- It requires the number of reflective elements  $8 \times 10^6$  to achieve 75% of the system capacity with  $\mu = 20$ . (Side length of the RIS should be  $\sim 10\text{m}$ )

# Case Study III: Orientation and Localization

## Reconfigurable Intelligent Surface (RIS) Assisted Wireless Coverage Extension: RIS Orientation and Location Optimization

S. Zeng, et al, "Reconfigurable Intelligent Surface (RIS) Assisted Wireless Coverage Extension: RIS Orientation and Location Optimization," IEEE Communications Letters, vol. 25, no. 1, pp. 269-273, Jan. 2021.

# Motivation and Contributions

## Problems

- RIS deployment has an influence on the cell coverage
- However, existing works only utilized the RIS for coverage extension given the RIS location, but how to deploy the RIS to maximize the cell coverage has not been studied.

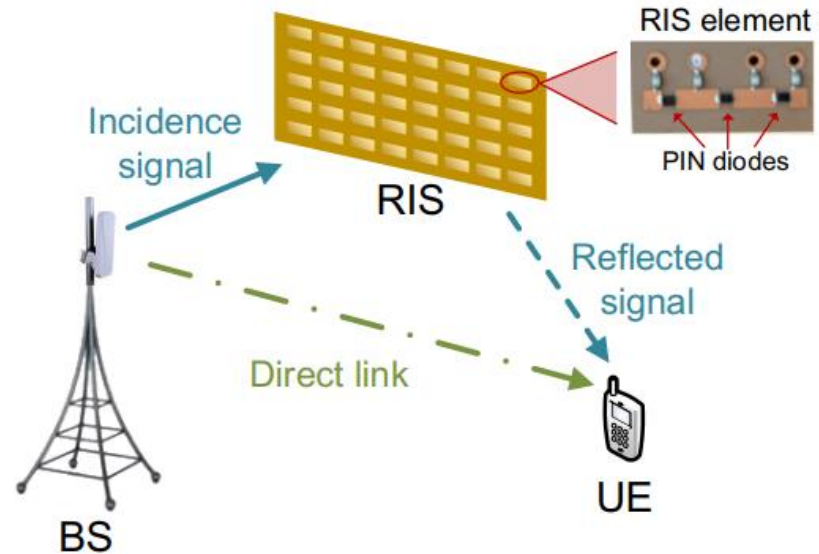
## Contributions

- We provide an analysis on the cell coverage of an RIS-assisted downlink cellular network
- The cell coverage is maximized by optimizing the RIS orientation and the horizontal distance between the RIS and the BS.

# System Model

## Scenario Description

- Single-cell downlink
- One BS, one UE, and one RIS
- Direct link and reflected links
- Small scale fading of channels is averaged



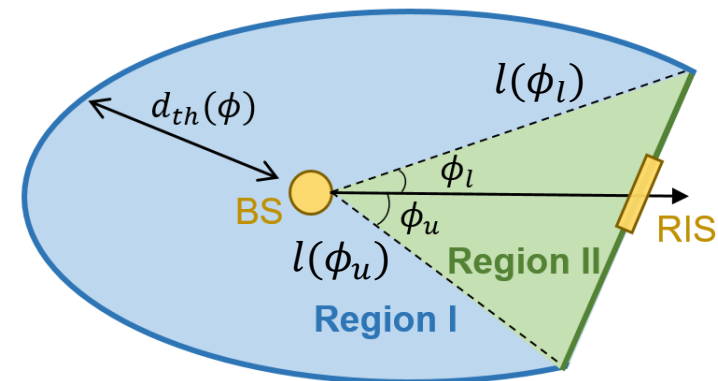
## Cell Coverage

- **Cell coverage** is an area where the received SNR is larger than a threshold
- It can be divided into **two regions**

coverage in direction  $\phi$

length of the boundary

$$S = \underbrace{\int_{\phi_l}^{\phi_u} \frac{1}{2} d_{th}^2(\phi) d\phi}_{\text{Region I}} + \underbrace{\frac{1}{2} \sin(\phi_l - \phi_u) l(\phi_l) l(\phi_u)}_{\text{Region II}}$$

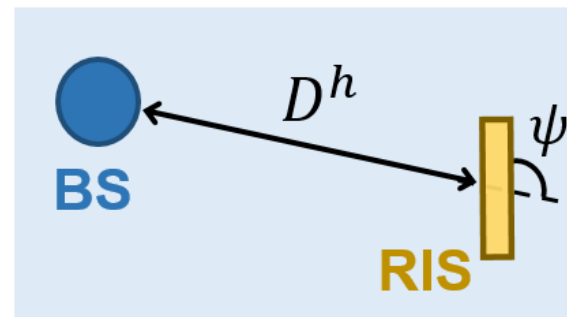




# RIS Placement Optimization

$$\max_{\underline{D^h}, \underline{\psi}} S = \int_{\phi_l}^{\phi_u} \frac{1}{2} d_{th}^2(\phi) d\phi + \frac{1}{2} \sin(\phi_l - \phi_u) l(\phi_l) l(\phi_u).$$

$\underline{D^h}$  → Horizontal distance  
 $\underline{\psi}$  → RIS orientation



## RIS Orientation Optimization

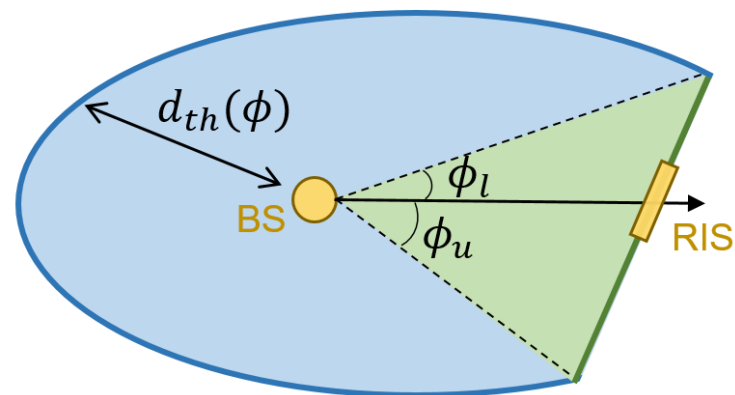
- For **any** horizontal distance, **optimal** RIS orientation:  $\psi = \frac{\pi}{2}$

## Horizontal Distance Optimization

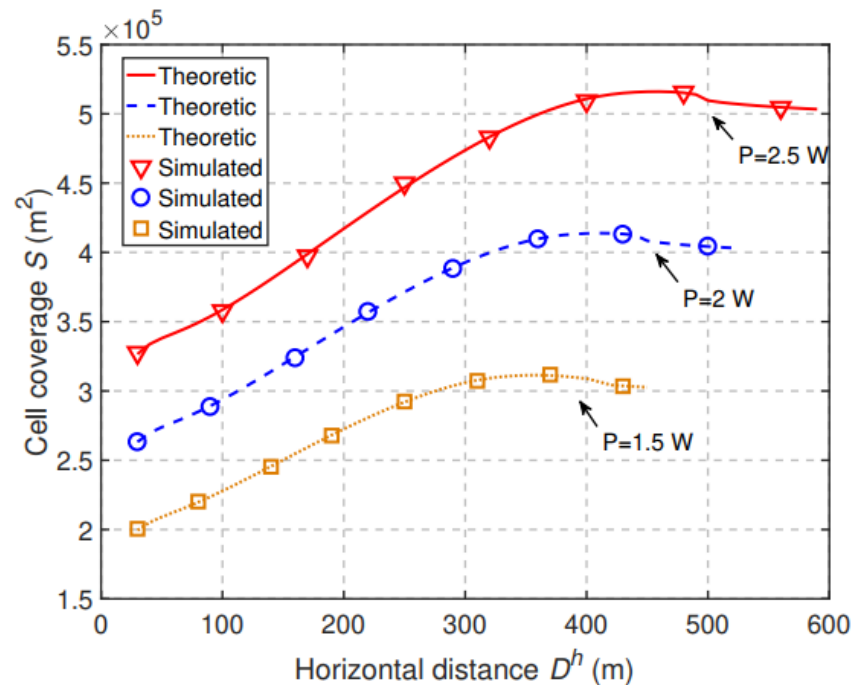
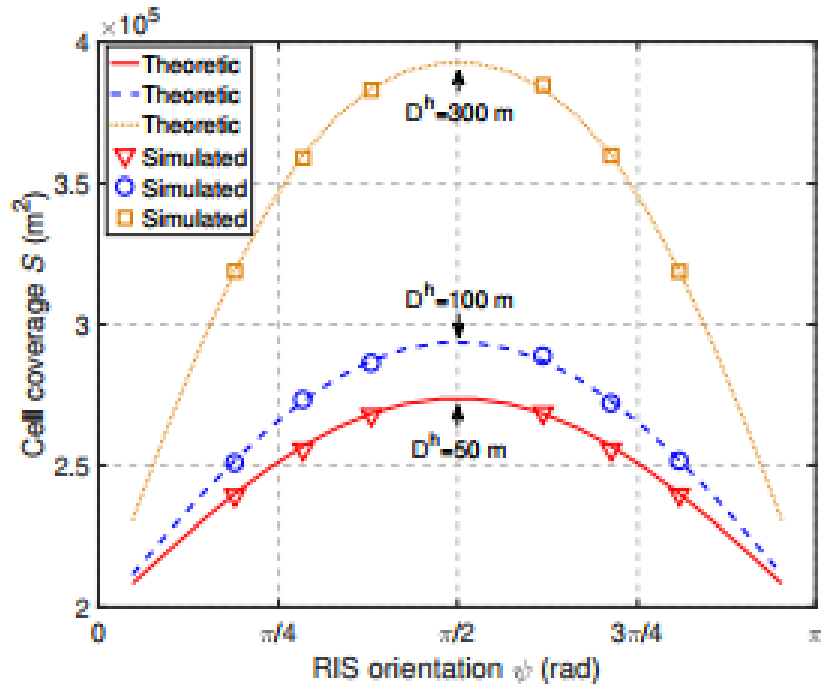
- $\phi_l, \phi_u, d_{th}(\phi)$  are coupled with  $D^h$
- $\phi_l, \phi_u, d_{th}(\phi)$  have no closed form results
- Discretize into  $K$  parts

$$\int_{\phi_l}^{\phi_u} \frac{1}{2} d_{th}^2(\phi) d\phi \approx \sum_{i=0}^{K-1} \frac{1}{2} d_{th}^2(\phi_l + i\Delta) \Delta,$$

- Solved by interior point method



# Simulation Results



- Simulation results are consistent with theoretical analysis
- The **optimal** RIS orientation is  $\frac{\pi}{2}$
- The RIS should be placed at **a moderate distance** from the BS to improve the cell coverage

# Case Study IV: RIS-aided Multi-User Communications

## Hybrid Beamforming for RIS based Multi-User Communications: Achievable Rates with Limited Discrete Phase Shifts

B. Di, et al, "Hybrid Beamforming for Reconfigurable Intelligent Surface based Multi-user Communications: Achievable Rates with Limited Discrete Phase Shifts," IEEE Journal of Selected Areas in Communications, vol. 38, no. 8, pp. 1809-1822, Aug. 2020.

# Motivation

## Problems

- RIS configuration:
  - **Multi-user** case: Inter-user interference exists
  - RIS elements **has limited discrete** phase shifts
- How to **perform the beamforming to maximize the sum rate?**

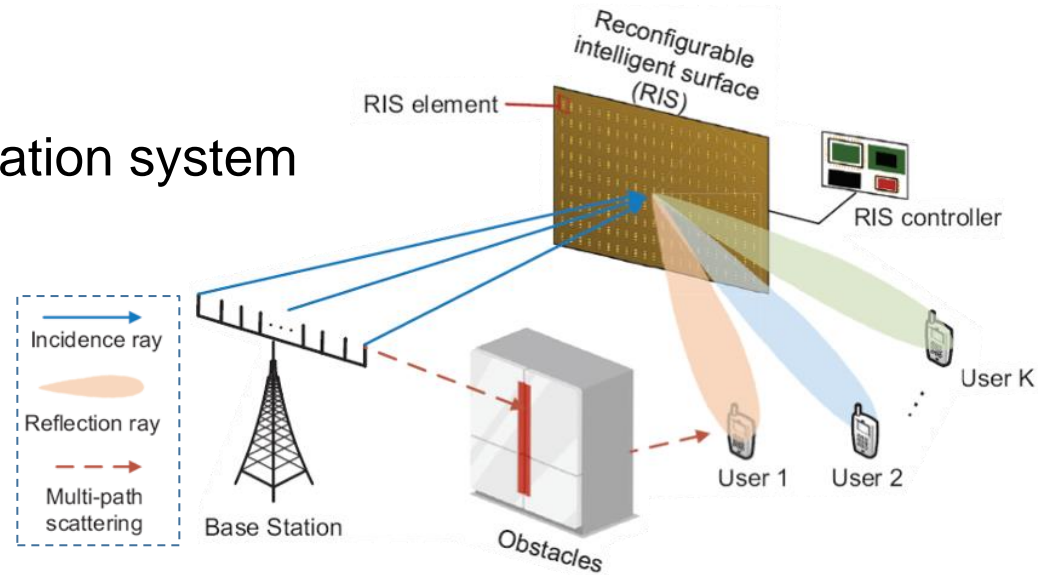
## Challenges

- The channel propagation and the RIS configuration are **coupled**.
- Discrete phase shifts render the sum rate maximization to be a NP-hard **mixed integer programming** problem.

# System Model

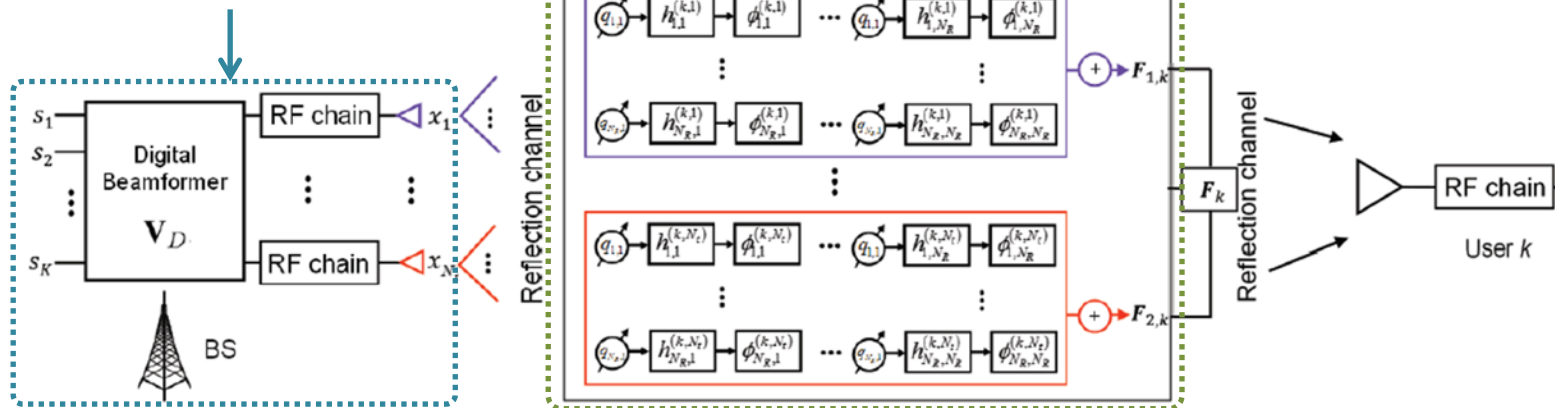
## System Model

- **Downlink multi-user** communication system
- $N_t$ -antennas BS
- $K$  single-antenna users
- $N_R \times N_R$  RIS elements
  - $b$ -bit quantization



## Hybrid beamforming

- RIS → analog beamforming
- BS → digital beamforming



# Problem Formulation

## Available Rate of User $K$

$$R_k = \log_2 \left( 1 + \frac{|\mathbf{F}_k^H \mathbf{V}_{D,k}|^2}{\sum_{k' \neq k} |\mathbf{F}_k^H \mathbf{V}_{D,k'}|^2 + \sigma^2} \right)$$

Channel coeff.

$$(\mathbf{F}_k)_n = \text{Tr}(\phi^{(k)} \mathbf{Q}^T \mathbf{H}^{(k,n)})$$

Analog beamforming (phase shifts)

Digital beamforming

## Sum Rate Maximization Problem

maximize  $\sum_{1 \leq k \leq K} R_k$   
 $\mathbf{V}_D, \{q_{l_1, l_2}\}$   
 subject to  $\text{Tr}(\mathbf{V}_D^H \mathbf{V}_D) \leq P_T,$   
 Phase shift constraint  $q_{l_1, l_2} = \frac{j + e^{j\theta_{l_1, l_2}}}{2}, 0$   
 Quantization constraint  $\theta_{l_1, l_2} = \frac{m_{l_1, l_2} \pi}{2^{b-1}}, 1$

*decouple*

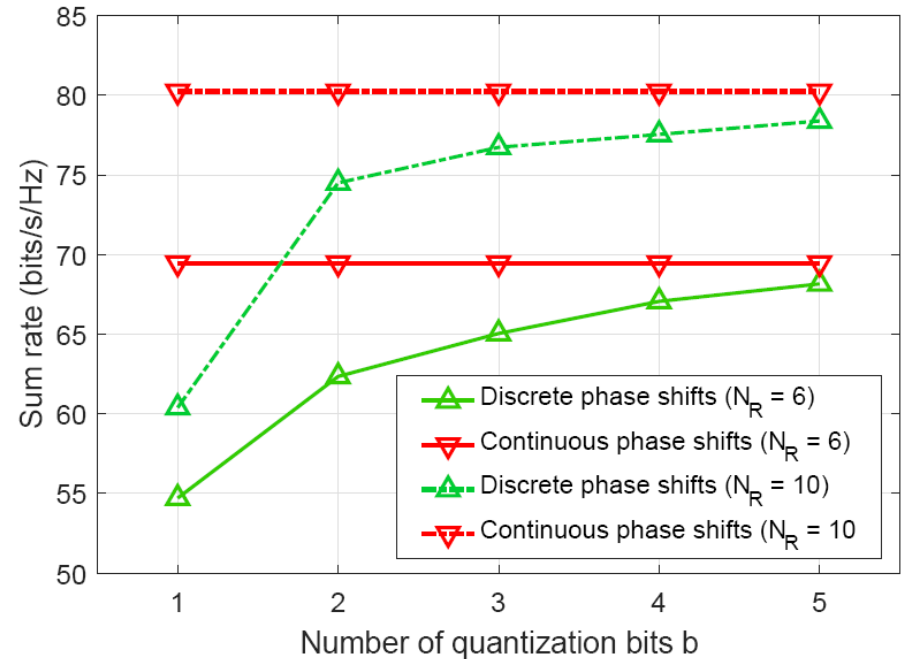
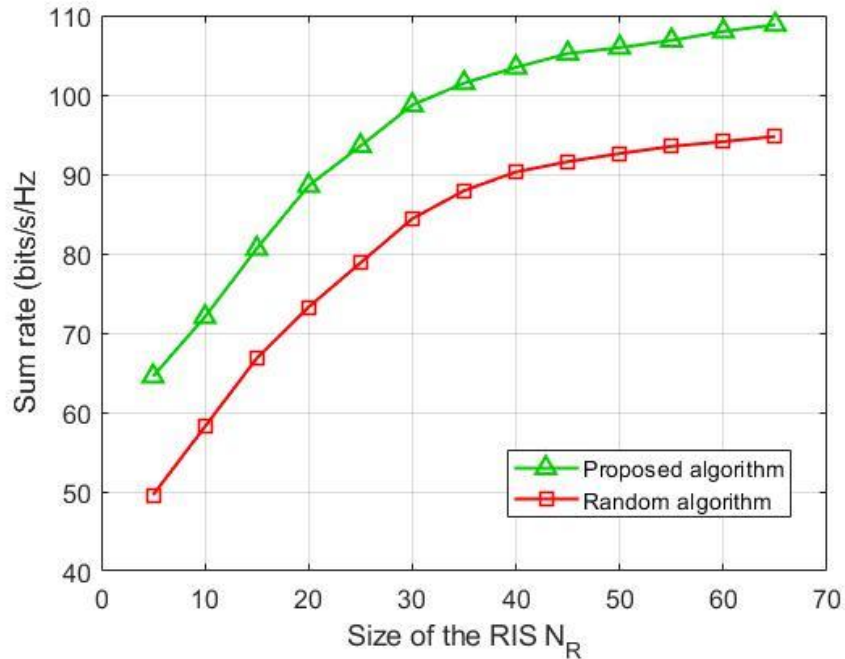
### Digital Beamforming Opt.

maximize  $\sum_{1 \leq k \leq K} R_k,$   
 $\mathbf{V}_D$   
 subject to  $\text{Tr}(\mathbf{V}_D^H \mathbf{V}_D) \leq P_T,$

maximize  $\sum_{1 \leq k \leq K} R_k,$   
 $\{\theta_{l_1, l_2}\}$   
 subject to  $\theta_{l_1, l_2} = \frac{m_{l_1, l_2} \pi}{2^{b-1}}$

### Analog Beamforming Opt.

# Simulation Results



- The sum rate grows rapidly with a small size of RIS and **gradually flattens** as the size of RIS continues to increase.
- As the number of quantization bits increases, the sum rate obtained by our proposed algorithm approaches that in the **continuous** case.

# Case Study V: Intelligent Omni-Surface

## Intelligent Omni-Surface: Ubiquitous Wireless Transmission by Reflective-Transmissive Metasurfaces

- ① S. Zhang et al, “Intelligent Omni-Surface: Ubiquitous Wireless Transmission by Reflective-Transmissive Metasurfaces,” IEEE Transactions on Wireless Communications, submitted.
- ② S. Zhang, H. Zhang, B. Di, Y. Tan, Z. Han, and L. Song, “Reflective-Transmissive Metasurface Aided Communications for Full-dimensional Coverage Extension,” IEEE Trans. Veh. Technol., vol. 69, no. 11, pp. 13905-13909, Nov. 2020.



# Motivations and Contributions

## Motivations

- Reflective RIS only serves users **on one side**, and shields the signals to the users on the other side
- We propose an **intelligent omni-surface (IOS)**-assisted downlink communication system, where the IOS transmits and reflects signals to the **users on both sides** simultaneously

## Challenge

- How to **control phase shifts of the IOS to serve users on two sides**

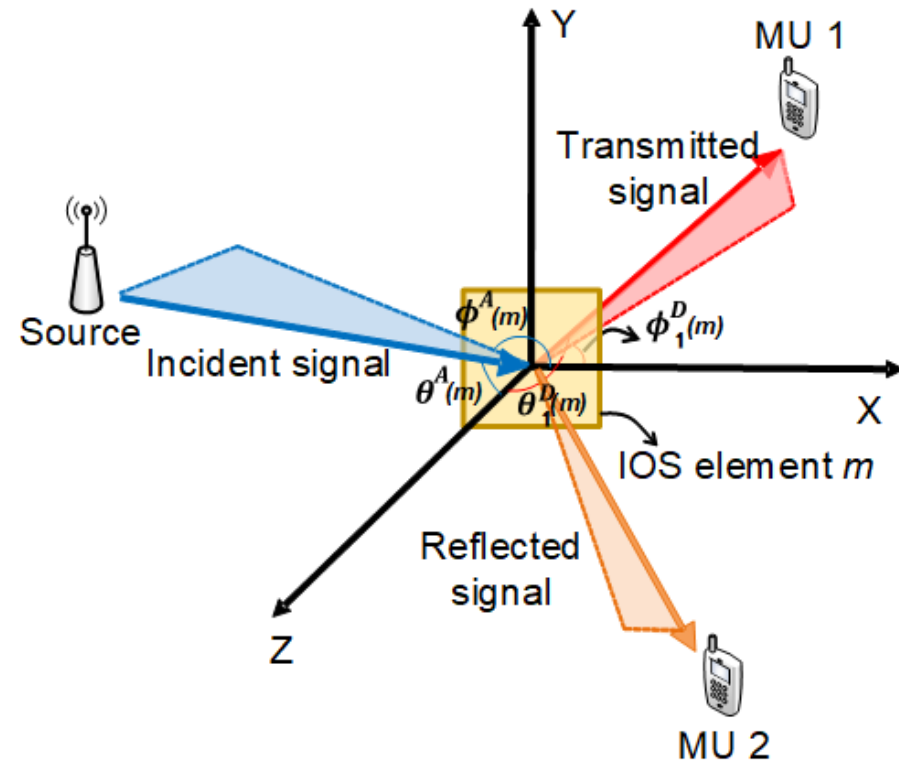
## Contributions

- We design the **BS digital beamforming and IOS beamforming** jointly to maximize the sum-rate of the system.
- We study the relation between the **optimal power ratio of the reflected and transmitted signals** and the **user distribution**.

# Signal Reflection-Transmission Model

## Model of a reflective-transmissive RIS element

- Transmitted signal:  $y = \sqrt{\frac{\varepsilon}{1+\varepsilon}} \Gamma e^{j\theta} x$
- Reflected signal:  $y = \sqrt{\frac{1}{1+\varepsilon}} \Gamma e^{j\theta} x$
- $\varepsilon$ : **Reflected-transmitted power ratio**
  - $\varepsilon = 0$ : Fully reflected
  - $\varepsilon \rightarrow \infty$ : Fully transmitted
- An element **reflects and transmits** signal simultaneously
- Reflective and transmissive signals through the same element have **the same phase shift**, but **different amplitudes**



# System Model and Problem Formulation

## System Model

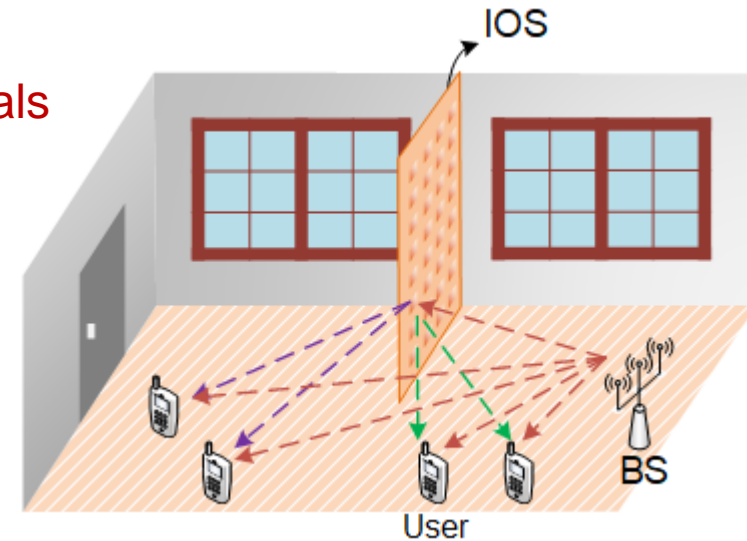
- **IOS**:  $M$  reflective-transmissive elements
- **Downlink** communication system
- $K$ -antennas BS
- $N$  single-antenna users distributed on two sides of the IOS
- Power radiation patterns of the IOS reflected and transmitted signals:

$$K_i^D(m) = \begin{cases} \frac{1}{1+\epsilon} |\cos^3 \theta_i^D(m)|, & \theta_i^D(m) \in (0, \pi/2), \longrightarrow \text{Reflected signals} \\ \frac{\epsilon}{1+\epsilon} |\cos^3 (\theta_i^D(m))|, & \theta_i^D(m) \in (\pi/2, \pi), \longrightarrow \text{Transmitted signals} \end{cases}$$

Power ratio of reflected and transmitted signals

## Problem Formulation

- Joint **BS digital beamforming** and **IOS beamforming design**
- Maximize **sum-rate** of all the users



# Problem Decomposition and Analysis

## Joint BS digital beamforming and IOS beamforming

- **NP-hard problem**, decouple into two sub-problems

Digital Beamforming  
Optimization at the BS

$$\max_{\mathbf{V}_D} \sum_{i=1}^N R_i,$$
$$s.t. \text{Tr}(\mathbf{V}_D \mathbf{V}_D^H) \leq P_B$$

BS transmission power constraint

Analog Beamforming  
Optimization at the IOS

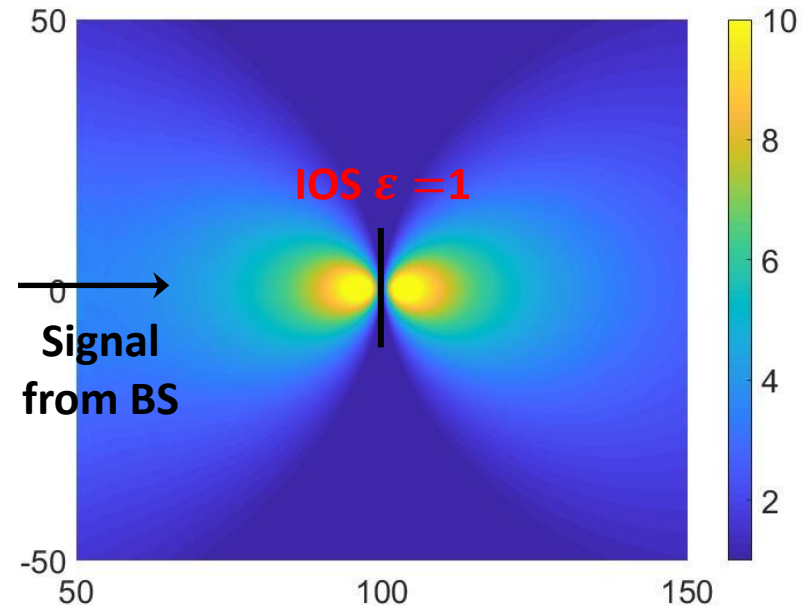
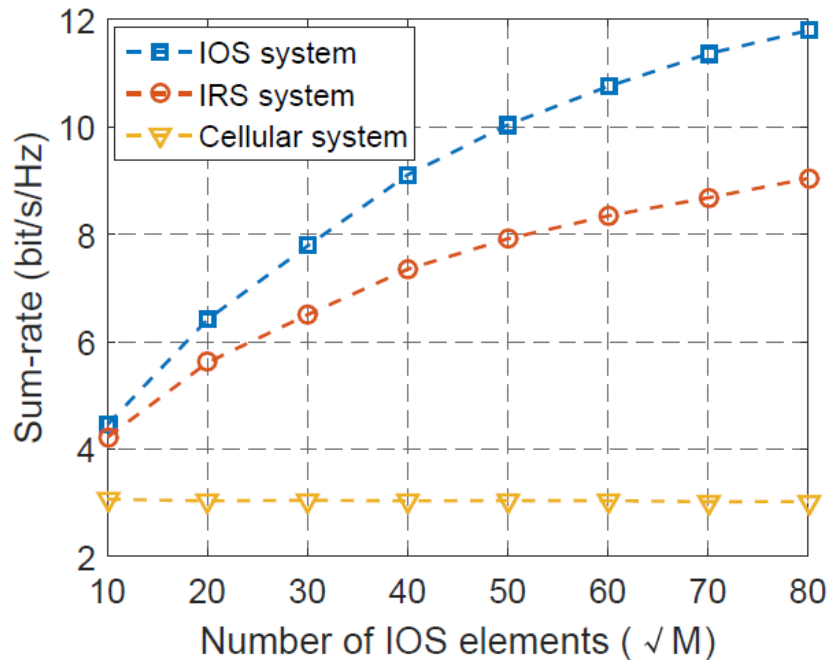
$$\max_s \sum_{i=1}^N R_i,$$
$$s.t. s_m \in \mathcal{S}_a, m = 1, 2, \dots, M.$$

Available phase shifts of IOS elements

## Analysis on reflected and transmitted signals

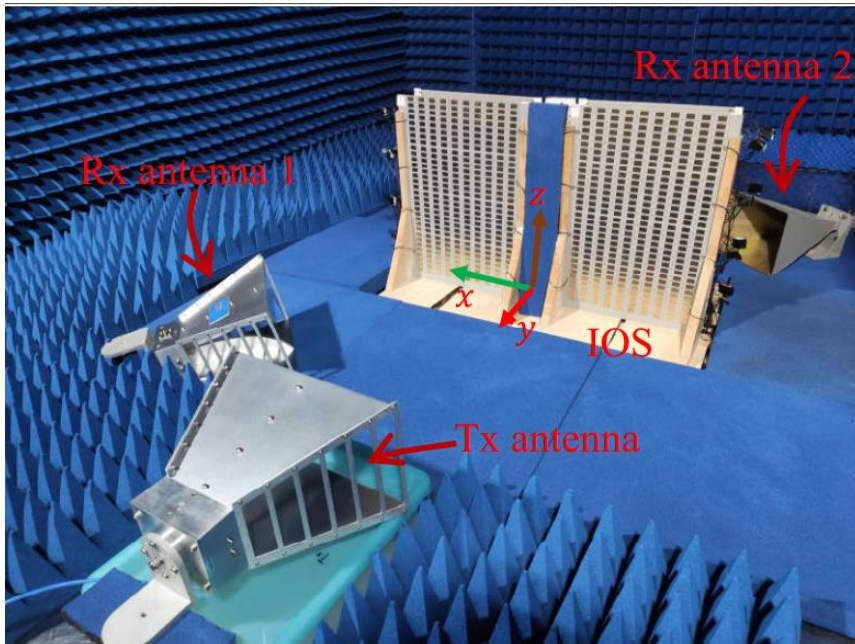
- The **optimal power ratio** of reflected and transmitted signals is positively correlated with **the number of users** on the two sides of the IOS
- To maximize the sum-rate, **larger proportion of the power** should be allocated to the users with **weaker direct links**

# Simulation Results

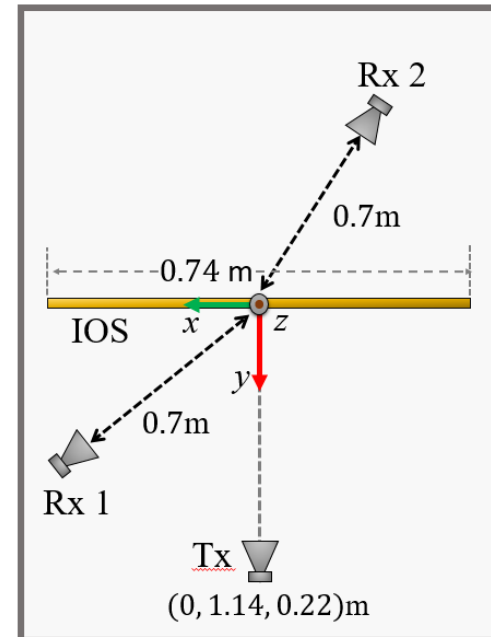


- IOS significantly improves the average sum-rate when compared to a conventional cellular, and can provide **30% higher sum-rate improvement than the reflective RIS**
- IOS can efficiently improve the downlink data rate on **both sides of it**

# Prototype of Intelligent Omni-Surface



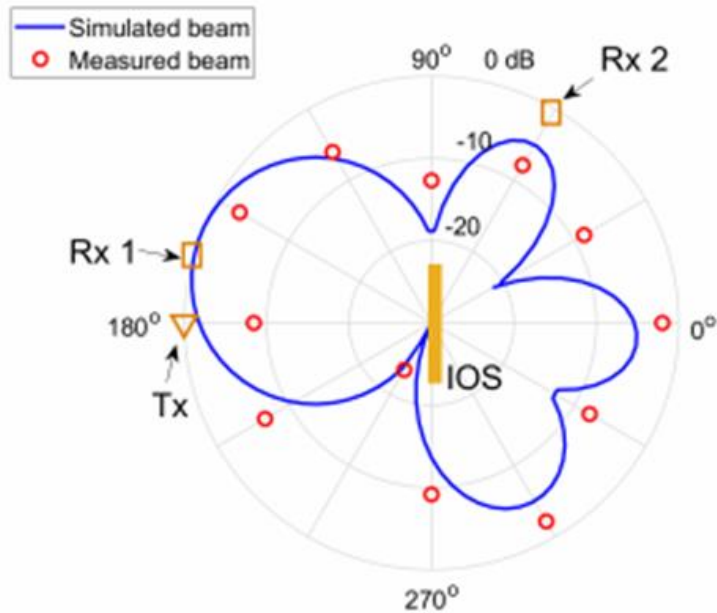
Full View



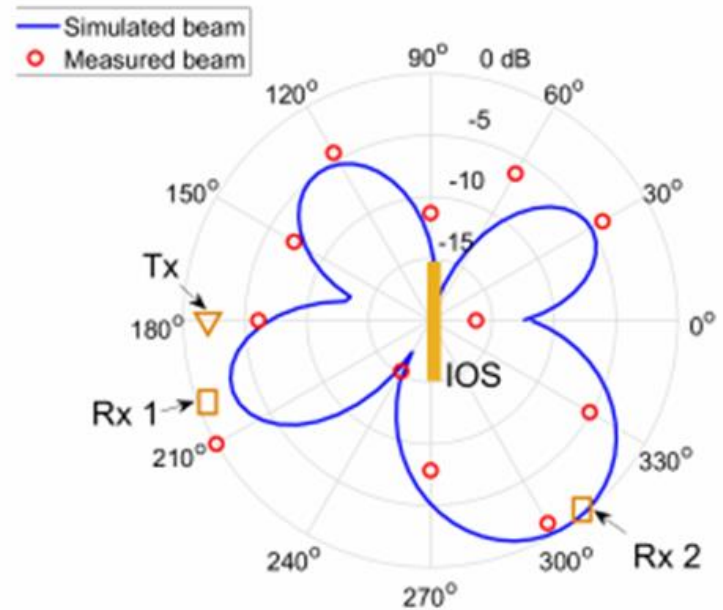
Top View

- Two Rxs: one on each side of the IOS
- Tx perpendicular to the IOS to reduce line-of-sight signals
- Implementation of IOS: 16 groups, 5\*8 elements in one group, and states of elements in one group are the same

# Initial Experimental Results



State 1



State 2

- The radiation pattern shows that the IOS can cover UEs on both sides
- By configuring the IOS state, the IOS can generate different beams

# Potential Directions

## **RIS-based Multi-cell / Multi-user Coordination**

- RIS-based D2D communications
- RIS-based NOMA
- RIS-based cell-free MIMO

## **Channel Estimation and Modelling**

- Semi-passive RIS channel estimation
- Passive RIS channel estimation

## **Other issues**

- Joint coding and transmission
- Physical-layer security
- Energy efficiency



# Table of Contents

## 1. Background

- 6G Communications and Requirements
- RIS Basics and Potential Applications

## 2. Mathematical Tools

- Optimization Theory
- Machine Learning

## 3. RIS-aided Cellular Communications

- Limited Phase Shifts Effect
- Size Effect
- Orientation and Localization
- RIS aided Multi-User Communications
- Intelligent Omni-Surface

## 4. RIS-aided RF Sensing

- RIS-aided Posture Recognition
- RIS-aided RF 3D Sensing
- RIS-aided Indoor Localization

# Background

- **RF sensing**

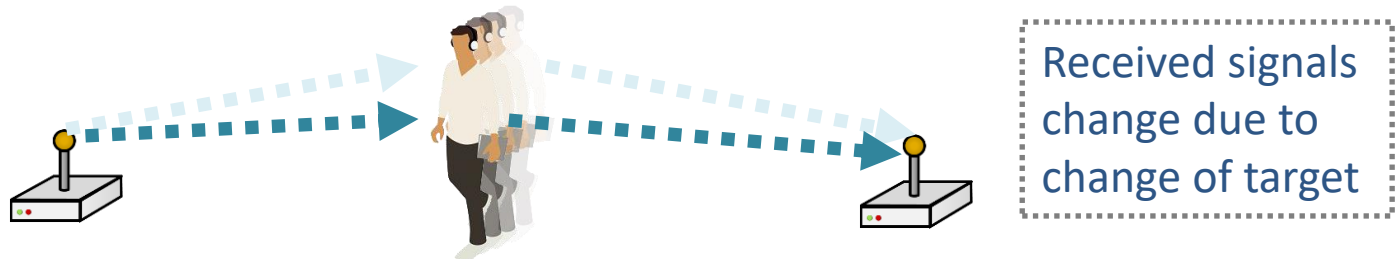
- Living environment is covered seamlessly by wireless signals
- Ubiquitous signals provide the foundation for RF sensing



Visualization of cellular signals

- **Principles:**

- Sensing targets between a pair of RF Tx and Rx **impact the RF channel**.
- The Rx can recognize different sensing targets by getting different received signals.



# Applications

## Security



Theft Detection



Theft detection

## Smart Space



Interaction



Emergency Alarm

## Safety



Fall Detection



Elderly Care

- **Advantages:**

- No needs for the contact or line-of-sight view of the sensing targets

# Techniques Review

- **Active Methods**
  - WiFi Sensing:
    - Utilize the impact of the targets on WiFi signals
    - Various metrics: signal strength, phase, doppler and so on
  - mmWave Radar:
    - Utilize the directional beams in mmWave communications
    - Receivers can detect reflected signals from targets
- **Limitations:** sensing accuracy is limited by channel conditions



Solution

- **Passive Method:** RIS-aided RF sensing

# Goals and Challenges

## Goals

- Implement practical RIS-aided RF sensing system for human and object localization and recognition
- Achieve high sensing accuracy

## Challenges

- Design **practical sensing protocols** to coordinate the RIS and the RF transceiver.
- Search the **optimal phase shift selection** for the RIS elements in a large feasible region.
- Propose **efficient algorithms** to obtain semantic meaning and location information of human and objects from received signals.

# Case Study VI: RIS aided Posture Recognition

## RIS-based RF Sensing: Design, Optimization, and Implementation

J. Hu, et al, "Reconfigurable Intelligent Surfaces based RF Sensing: Design, Optimization, and Implementation," IEEE Journal of Selected Areas in Communications, vol. 38, no. 11, pp. 2700-2716, Nov. 2020.

# Motivation

## RIS-based RF sensing system

- RIS can **control the wireless environment**, which can provide favorable wireless environment for RF sensing.
- Application in human posture recognition:
  - Recognize different human postures automatically

## Challenges

- RIS configuration design – *How RIS controls the wireless environment*
  - **The discrete phase shifts of a massive number of RIS elements** need to be determined.
- Decision function design – *How Rx judges human posture*
  - The integration of the RIS makes the relationship between Rx signals and human posture more complicated.
- Moreover, RIS configuration and decision function are **coupled**.

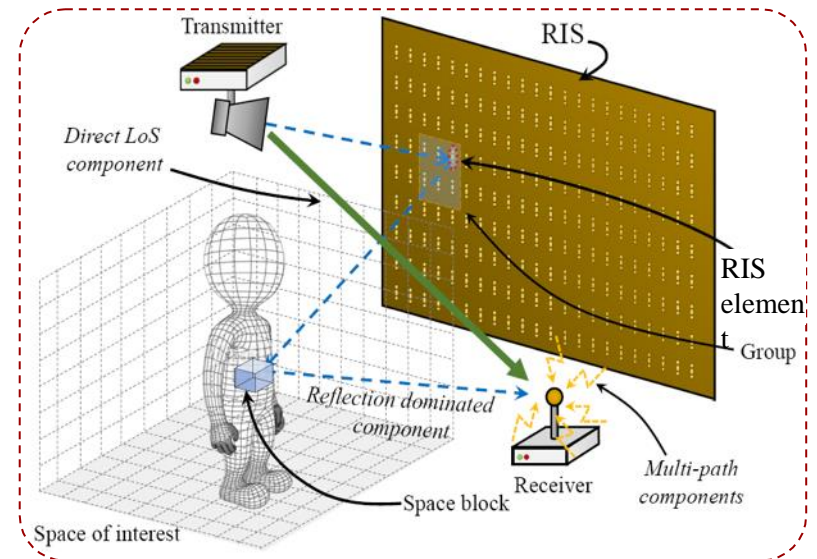
# Model Description

## System Structure

- Transmitter: A **directional antenna** which is pointed towards the RIS
- Receiver: An **omni-directional vertical antenna** below the RIS
- Human: **Space reflection** vector carries the information of postures.
- RIS: RIS elements in the same group are **in the same state**.

## Channel Model

- Multi-path component:
  - Environment scattering
- LoS component:
  - Transmitter → Receiver
- Reflection dominated components
  - Transmitter → RIS → Human → Receiver





# Periodic Configuring Protocol

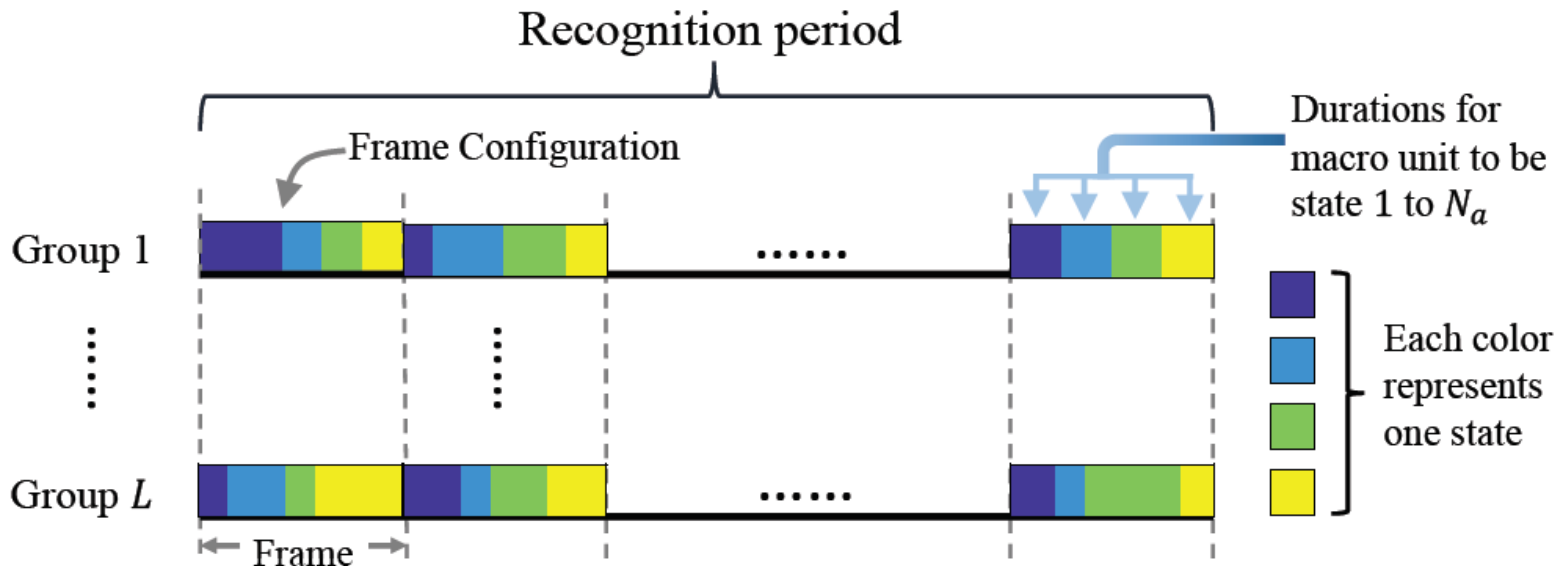
## Recognition Period:

- Contains  $K$  frames, during which the **human posture is fixed**
- Received signals during a recognition period are used for recognition

## Frame Configuration:

Different **states** correspond to different **phase shifts**

- Each group of RIS elements **sequentially** changes from **State 1** to  $N_a$ .
- Constituted by **the durations that each group stays in the  $N_a$  states**



# Problem Formulation

**Decision Function:** The receiver uses the decision function to generate the probabilities for deciding on different human postures.

**Optimization Problem:** Minimize the false recognition cost

$$(P1) \min_{\mathbf{T}, \mathcal{L}} C_{FR}(\mathbf{T}, \mathcal{L}) = \sum_{i, i'} \underbrace{\Pr(\text{pos}_i)}_{\text{Probability of Posture } i \text{ to appear}} \cdot \underbrace{\text{cost}(i, i')}_{\text{Cost for recognizing Posture } i \text{ as } i'} \cdot \mathbb{E}_{\mathbf{y}}[\underbrace{\Pr(\mathbf{y}|\text{pos}_i)}_{\mathbf{y}: \text{Measured signals in a period}} \cdot \underbrace{\mathcal{L}_{i'}(\mathbf{y})}_{\mathcal{L}_{i'}(\mathbf{y}): \text{Probability for deciding on Posture } i' \text{ given } \mathbf{y}}]$$

## Optimization Variables

$\mathbf{T}$ : Frame configurations in a recognition period

$\mathcal{L}$ : Decision function

Probability of Posture  $i$  to appear

Cost for recognizing Posture  $i$  as  $i'$

$\mathbf{y}$ : Measured signals in a period

$\mathcal{L}_{i'}(\mathbf{y})$ : Probability for deciding on Posture  $i'$  given  $\mathbf{y}$

## Problem Decomposition:

- Decomposing (P1) into the frame configuration optimization and the decision function optimization.

$C_{FR}(\mathbf{T}, \mathcal{L})$   
Coupled optimization objective in (P1)

$C_{FR}(\mathbf{T})$

RIS frame configuration optimization objective

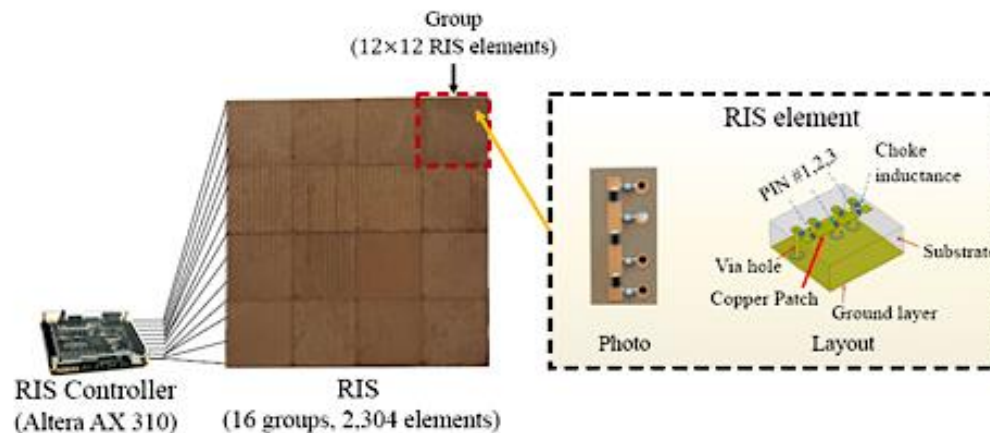
$C_{FR}(\mathcal{L})$

Decision function optimization objective

# Implementation

## RIS & RIS Control Circuit

- **Size of RIS:**  $69 \times 69 \times 0.52 \text{ cm}^3$
- **Dielectric substrate:** Rogers 3010 (dielectric constant:  $\epsilon = 10.2$ )
- **PIN diodes:** BAR 65-02L  $\times 3$
- **Total number of possible phase shifts:** 8
  - Four of them are used with phase shifts  $(\frac{\pi}{8}, \frac{3\pi}{8}, \frac{5\pi}{8}, \frac{7\pi}{8})$
- **RIS controller:** FPGA ALTERA-AX301



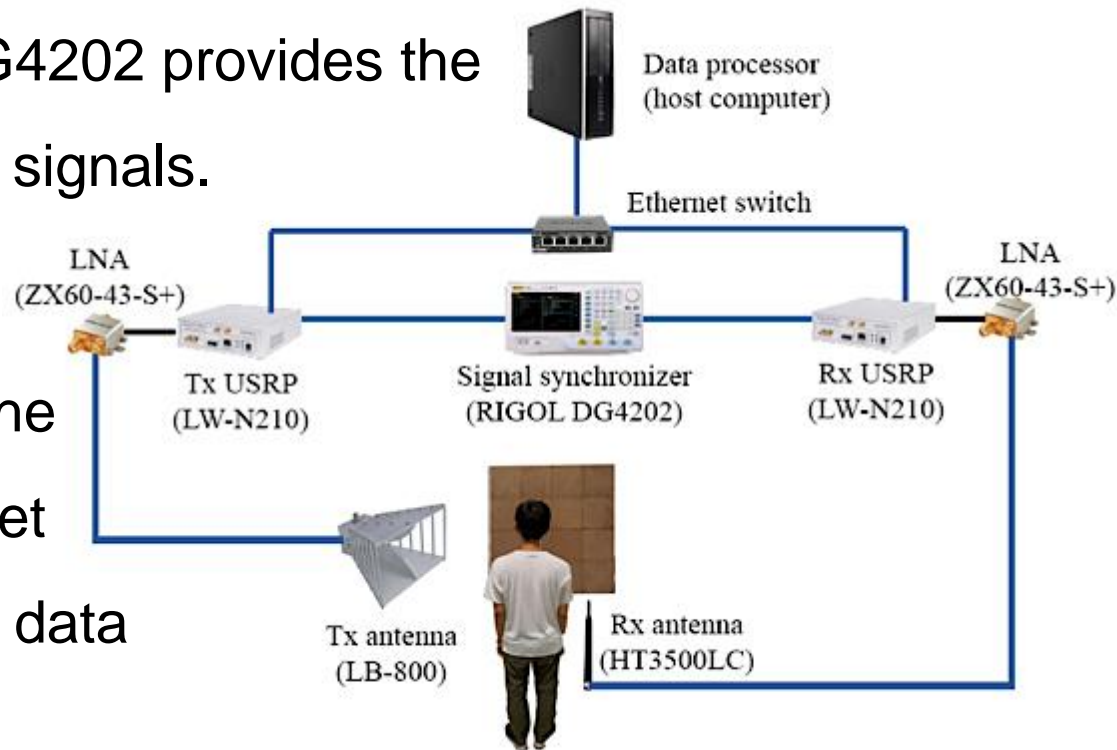
# Implementation

## RF Circuit

- **Baseband Processor:** USRPs LW-N210
- **RF Board:** SBX-120W (0-6GHz, Max Power = 100mW)
- **Amplifier:** ZX60-43-S+ (Gain around 17dB)
- **Synchronizer:** RIGOL DG4202 provides the pps and clock signals.

## Date Processor

- Host computer connects the Tx/Rx USRPs with Ethernet to send/receive baseband data



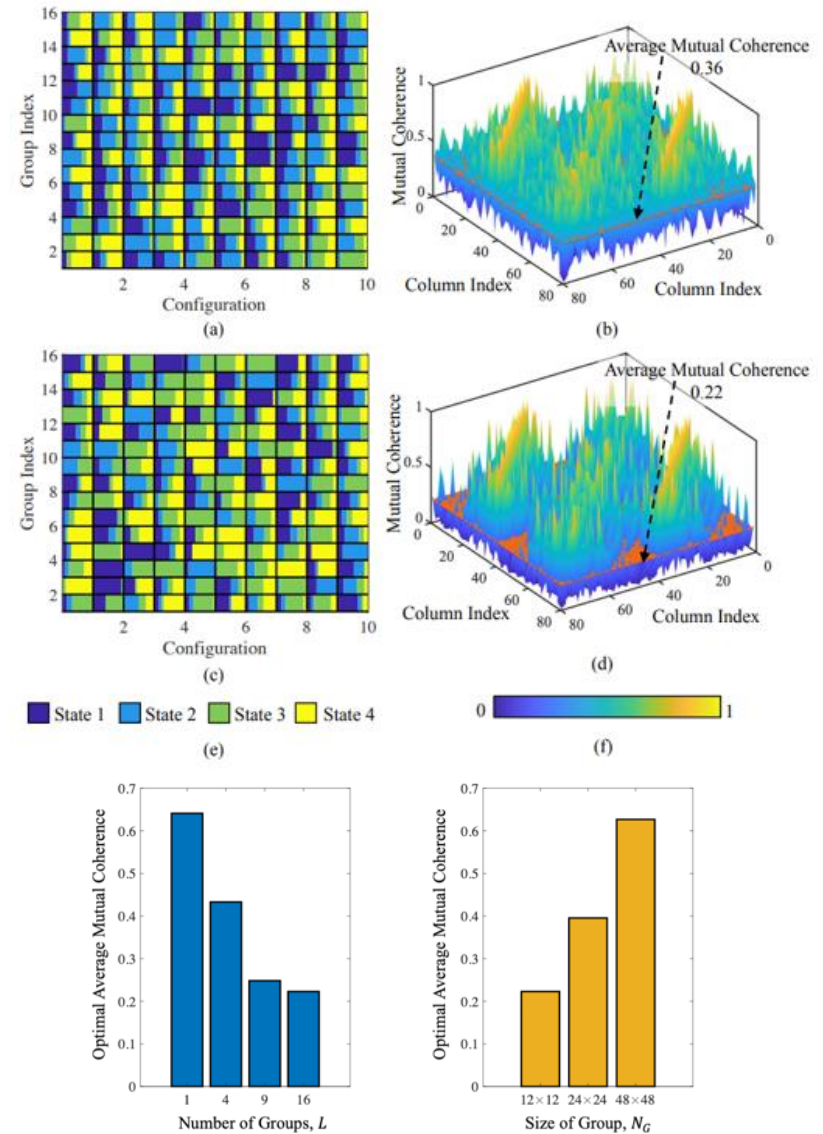
# Experimental Results

## Effectiveness:

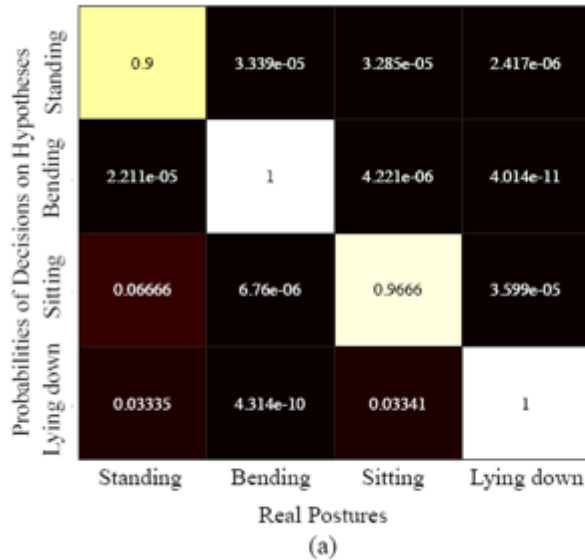
- The average mutual coherence of the measurement matrix is reduced, which can improve sensing accuracy.

## Insights:

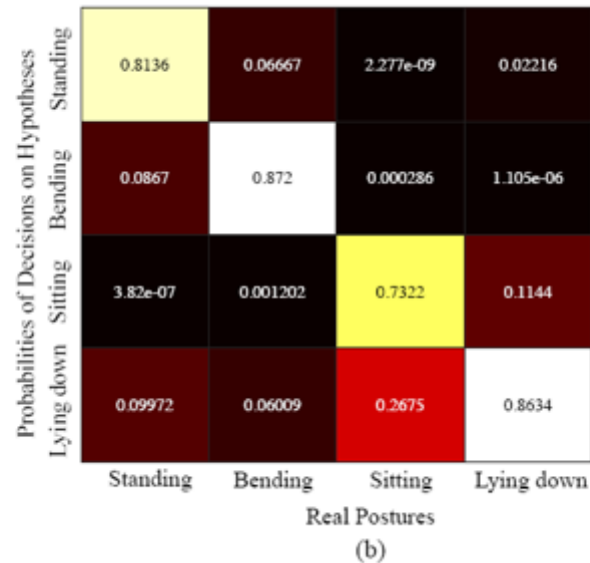
- The optimized average mutual coherence decreases with the number of groups that the RIS contains, i.e., the size of the RIS.
- The optimal average mutual coherence increases with the size of groups.



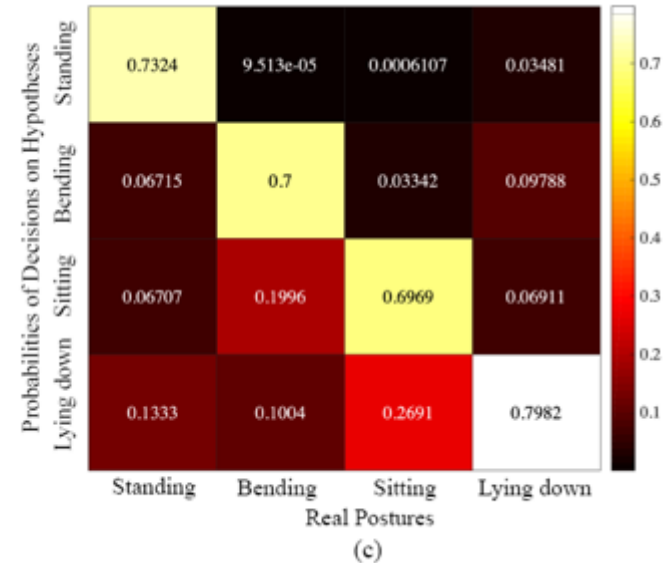
# Experimental Results



Proposed method



Random method



Without RIS method

- Compared with traditional RF sensing systems, RIS **increases** the posture recognition accuracy with **23.5%**.
- Compared with the system with random frame configurations, the system with optimized frame configurations achieves **14.6% higher** recognition accuracy.

# Case Study VII: RIS aided RF 3D Sensing

## MetaSensing: Intelligent Metasurface Assisted RF 3D Sensing by Deep Reinforcement Learning

J. Hu, et al, "MetaSensing: Intelligent Metasurface Assisted RF 3D Sensing by Deep Reinforcement Learning," IEEE Journal of Selected Areas in Communications, under review.

# Motivation

## RF 3D sensing:

- From optical images, the complete information about 3D objects is hard to acquire due to the blocking of themselves.
- RF signals can detect these space of objects by reflection and scattering, which makes 3D sensing possible from RF signals

## RIS-based 3D sensing

- The RIS **controls RF signal beams** by manipulating configuration
- Using controlled RF signal beams, the RIS can obtain more information about 3D objects in space and construct their shapes.

## Challenges

- How to optimize the RIS's configuration to create favorable propagation channels for sensing
- How to obtain the mapping from RF signals to 3D shapes.



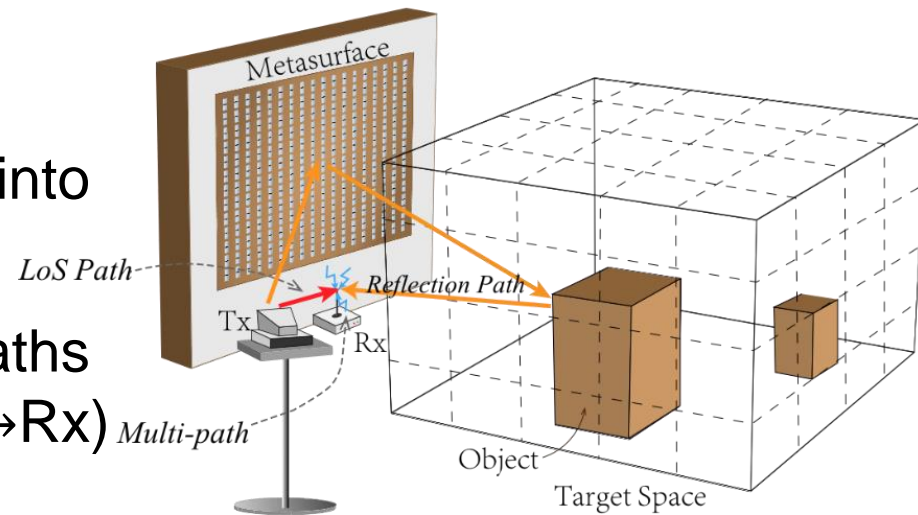
# Model Description

## System Description

- **Transmitter:** A **directional antenna** which is pointed towards the RIS
- **Receiver:** An **omni-directional vertical antenna** below the RIS
- **RIS:** Contains  $N$  meta-elements, each with  $N_S$  phase shifts
- **Sensing Target:** Existence of objects at  $M$  space grids

## Channel Model

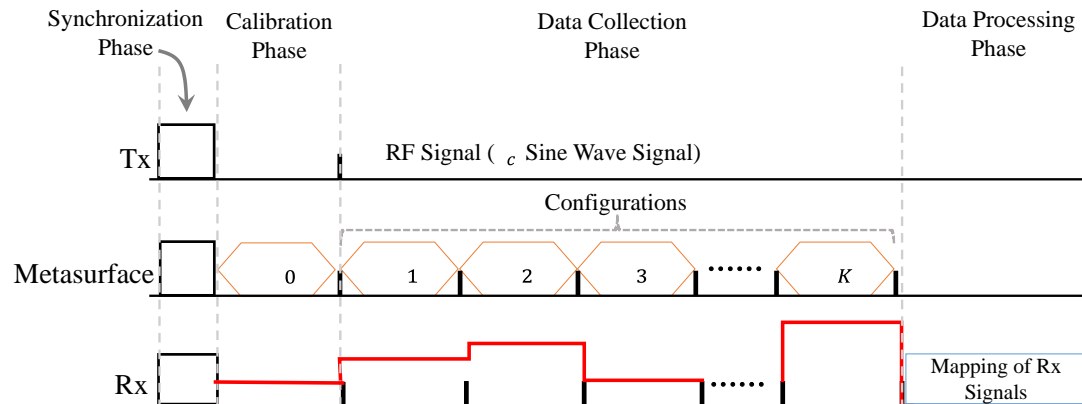
- The target space is discretized into  $M$  space grids.
- The total  $N \times M$  reflection paths (Tx  $\rightarrow$   $N$  RIS elements  $\rightarrow$   $M$  grids  $\rightarrow$  Rx) are summed at the Rx



# Sensing Protocol

## RF Sensing Protocol

- **Synchronization Phase:** synchronizes the Tx transmission, the RIS's configuration changes, and Rx reception
- **Calibration Phase:** the RIS is in  $c_0$  (no phase shifts incurred), and the received signal is used to **subtract the environmental scattering**.
- **Data Collection Phase:** RIS **changes its configuration with equal time interval**, and the Rx averages the received signals in each config.
- **Data Processing Phase:** The Rx use **a decision function** to determine the objects' existence at different space grids.



# Problem Formulation

**Decision Function:** The Rx use the mapping function  $f^w$  to estimate the probabilities for objects to be at  $M$  space grids, i.e.,  $\hat{\mathbf{p}} \in [0,1]^M$ .

**Optimization Problem:** Minimize the *cross-entropy (CE) loss* given configuration matrix  $\mathbf{C}$  and mapping function parameters  $\mathbf{w}$

**Entropy of Ground Truth**  
 $p_m$ : true probability of m-th grid being non-empty

**Entropy of Estimation**  
 $\hat{p}_m$ : estimated probability of m-th grid being non-empty

$$(P1) : \min_{\mathbf{C}, \mathbf{w}} - \mathbb{E}_{\mathbf{p}} \left[ \sum_{m=1}^M p_m \cdot \ln(\hat{p}_m) + (1 - p_m) \cdot \ln(1 - \hat{p}_m) \right],$$

*s.t.*  $(\hat{p}_1, \dots, \hat{p}_M) = f^w(\tilde{\mathbf{y}}),$

- $\tilde{\mathbf{y}} = \sqrt{P} \cdot \mathbf{x} \cdot (\mathbf{C} - \mathbf{C}_0) \mathbf{A} + \tilde{\boldsymbol{\sigma}},$
- $\mathbf{C} = (\mathbf{c}_1^T, \dots, \mathbf{c}_K^T)^T,$
- $\mathbf{c}_k = (\hat{\boldsymbol{\sigma}}(c_{k,1}), \dots, \hat{\boldsymbol{\sigma}}(c_{k,N})), \forall k \in [1, K],$
- $c_{k,n} \in [1, N_S], \forall k \in [1, K], n \in [1, N].$

**Constraints**

(1) Estimation is obtained by mapping of received signals  $\rightarrow$

(2) Rx signal is determined by RIS configuration  $\mathbf{C}$   $\rightarrow$

(3) Config.  $\mathbf{C}$  consists of the phase shifts of the  $N$  RIS elements in  $K$  time intervals  $\rightarrow$

**Challenge :**

- Optimization of config.  $\mathbf{C}$  and mapping  $f^w$  are **highly coupled**.

# Algorithm Design

- Decompose (P1) into **configuration optimization** and **mapping function optimization** problems

*Coupled optimization objective in (P1)*

*RIS configuration optimization (sP1)*

$$CE(\mathbf{C}, \mathbf{f}^{\mathbf{w}})$$

*Mapping function optimization (sP2)*

$$CE(\mathbf{C}) | \mathbf{f}^{\mathbf{w}}$$

$$CE(\mathbf{f}^{\mathbf{w}}) | \mathbf{C}$$

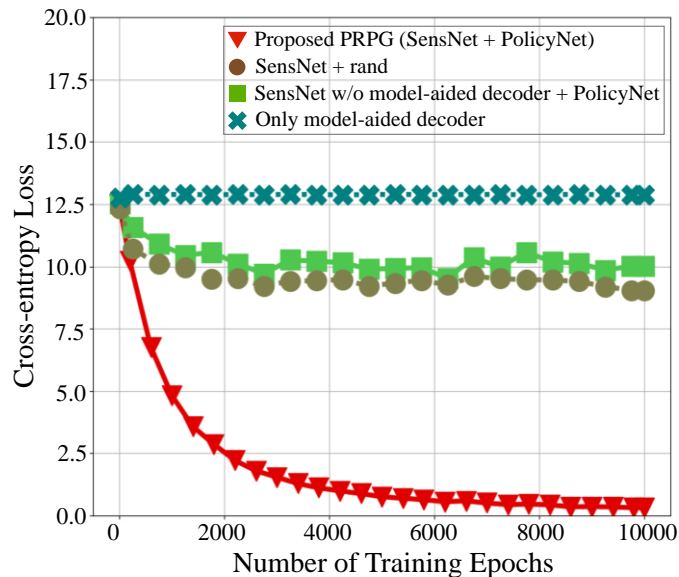
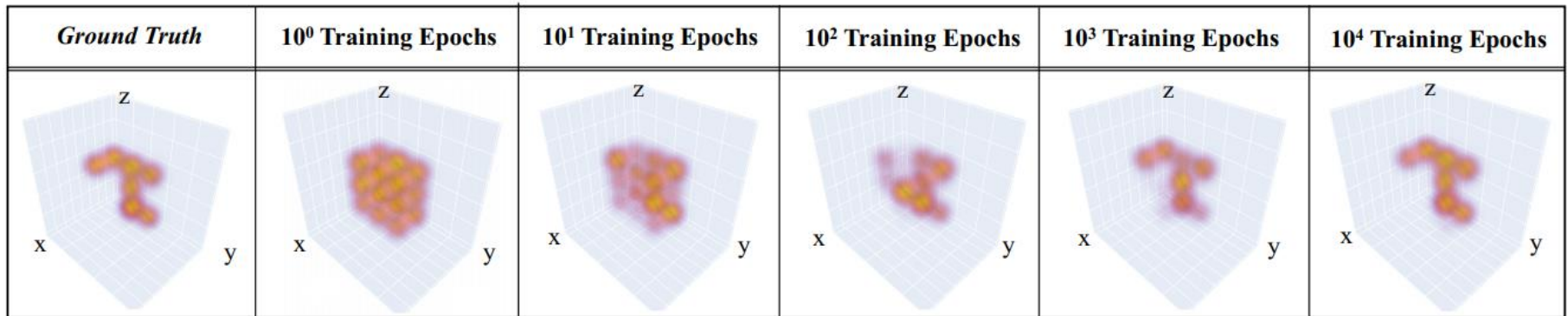
**Challenge:** Configuration matrix  $\mathbf{C}$  is an integer matrix and has a large number of elements.

**Solution:** Propose a deep reinforcement learning algorithm which can find the optimal policy for selecting  $\mathbf{C}$ .

**Challenge:** Mapping function  $\mathbf{f}^{\mathbf{w}}$  has unknown form and parameter  $\mathbf{w}$ .

**Solution:** Model  $\mathbf{f}^{\mathbf{w}}$  by a neural network depicting an arbitrary function and propose a supervised learning algorithm to train  $\mathbf{w}$ .

# Simulation Results



- Sensing results of a 3D object **gets close quickly to the ground truth** as the training proceeds
- The proposed algorithm converges with a high speed
- The proposed algorithm results in the **lowest CE loss** among all benchmark algorithms.

# Case Study VIII: RIS aided Localization

## Towards Ubiquitous Positioning by Leveraging RIS

- ① H. Zhang, et al, “Towards Ubiquitous Positioning by Leveraging Reconfigurable Intelligent Surface,” IEEE Commun. vol. 25, no. 1, pp. 284-288, Jan. 2021.
- ② H. Zhang, et al, “MetaRadar: Indoor Localization by Reconfigurable Metamaterials,” IEEE Trans. Mobile Comput., to appear. Arxiv: <https://arxiv.org/abs/2008.02459>.

# Background

## **Radio Frequency (RF) based Positioning:**

- Applications: Navigation, healthcare monitoring, indoor positioning
- Categories:
  - Received signal strength (RSS)
  - Channel state information (CSI)
  - Angle-of-arrival (AoA)
  - Time-of-arrival (ToA)

## **RSS based Positioning:**

- Advantages: simplicity of measuring RSS and minimum hardware requirements
- Principle: users' locations are obtained by comparing the measured RSS and the stored **RSS distribution** in the indoor environment.

# Motivation

## Limitations of Traditional Methods

- The RSS distribution is passively measured and **cannot be customized**
- The localization performance degrades if RSS values are **similar** to each other in the RSS distribution

## RIS aided Positioning:

- Users receive the signals from the AP and the RIS.
- RIS adjusts the RSS distribution by changing its **configuration**.

## Challenges

- Localization protocol design: coordination among the RIS, AP and users.
- RIS configuration design
  - **Large number** of RIS configurations.
  - **Complicated relation** between the RIS configuration and the RSS distribution.



# System Model

## Positioning Scenario

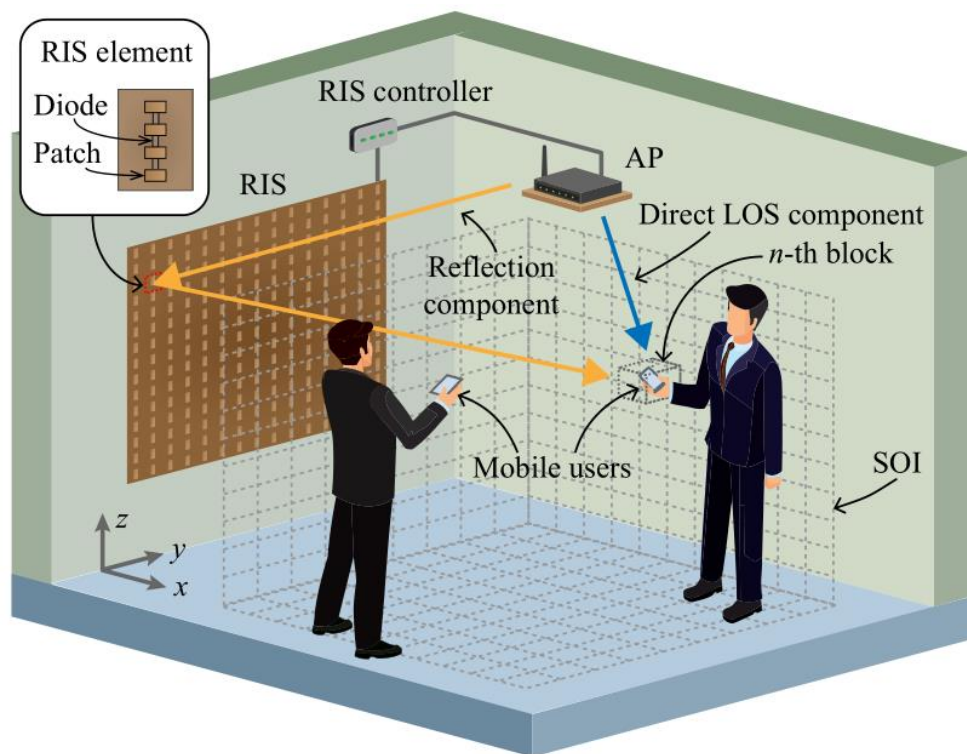
- AP: sends signals to the RIS and mobile users.
- RIS: reflects the signals from the AP to the users.
- Users: measure the RSS for positioning.
- Space of Interest (SOI): is discretized into  $N$  blocks to represent users' positions.

## RIS Model

- $M$  elements.
- Each element has  $C$  states with different reflection coefficients.

$$r_m(c_m) = \underbrace{r(c_m)}_{\text{Amplitude}} e^{-j \underbrace{c_m \Delta \theta}_{\text{Phase shift}}}$$

- Configuration  $c$ : the vector of all the elements' states



# System Model

## RSS Model

- Direct LOS channel  $h_{lo}$ : AP  $\rightarrow$  User at the  $n$ -th block
- Reflection channel  $h_{m,n}(c_m)$ : AP  $\rightarrow$  element  $m$   $\rightarrow$  User at the  $n$ -th block

$$h_{m,n}(c_m) = \frac{\lambda}{4\pi} \cdot \frac{\sqrt{g_m^t g_{m,n}^r} r_m(c_m) e^{-j2\pi(l_m^r + l_{m,n}^r)/\lambda}}{l_m^r l_{m,n}^r}$$

Wavelength of the RF signal    
 Power gains of AP and user antennas    
 Distance between AP and the  $m$ -th element    
 Distance between the  $m$ -th element and the user

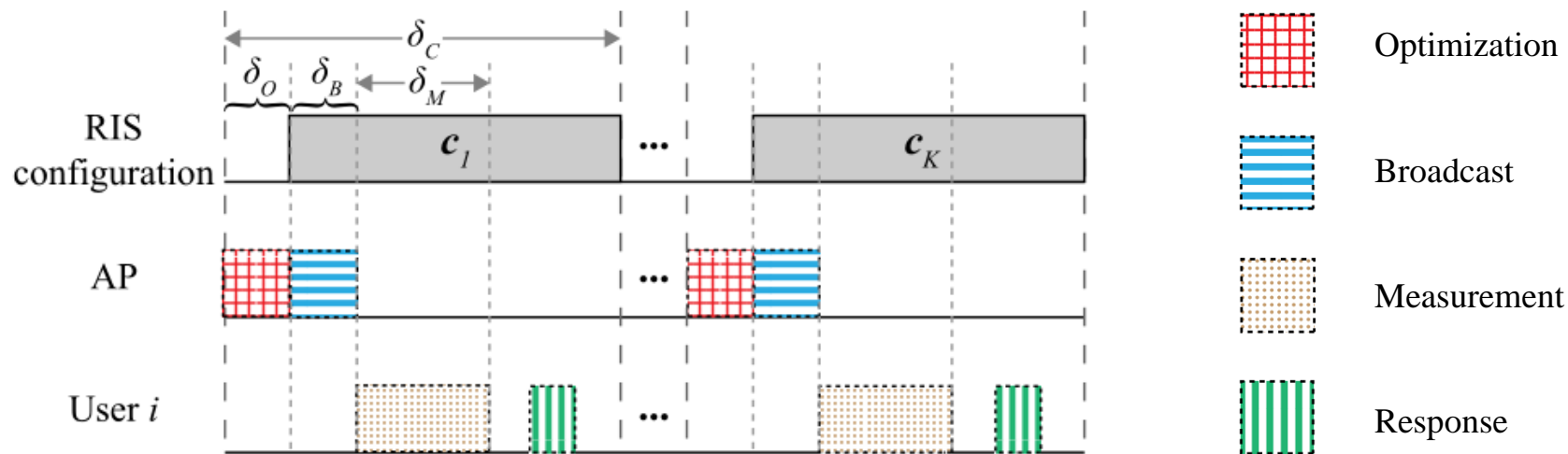
- RSS at the  $n$ -th block under configuration  $\mathbf{c}$

$$s_n(\mathbf{c}) = \underbrace{s^t}_{\text{Transmission power of AP}} + 20 \log_{10} \left| h_{lo} + \sum_{m \in \mathcal{M}} h_{m,n}(c_m) \right| + \underbrace{\xi}_{\text{Log-normal shadowing component}}$$

# Positioning Protocol

The positioning process has  $K$  cycles, and each cycle contains four steps:

- **Optimization:** AP selects the optimal configuration  $c_k$  for this cycle.
- **Broadcast:** AP broadcasts  $c_k$  to users and the RIS.
- **Measurement:** AP sends single-tone signal with frequency  $f_c$ , and users record the RSS under configuration  $c_k$ .
- **Response:** Users send the RSS information to the AP.



# Problem Formulation

**Objective:** Minimize the **average positioning loss** (weighted probabilities of false positioning) in every cycle.

$$l(\mathbf{c}^k) = \sum_{i \in I} \sum_{\substack{n, n' \in \mathcal{N} \\ n \neq n'}} p_{i,n}^k \gamma_{n,n'}^k \int_{\mathcal{R}_{i,n'}^k} \mathbb{P}(s_i^k | \mathbf{c}^k, n) \cdot ds_i^k$$

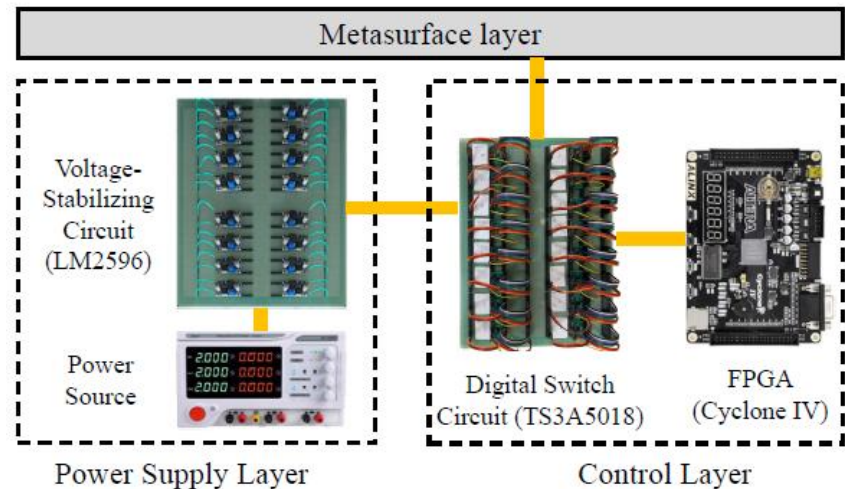
- $p_{i,n}^k$ : prior probability that user  $i$  is at the  $n$ -th block in the  $k$ -th cycle.
- $\gamma_{n,n'}^k$ : loss parameter when the positioning result is the  $n'$ -th block while the user is at the  $n$ -th block.
- $\mathbb{P}(s_i^k | \mathbf{c}^k, n)$ : probability that user  $i$  receives  $s_i^k$  under  $\mathbf{c}^k$  at the  $n$ -th block.
- $\mathcal{R}_{i,n'}^k$ : decision region for block  $n'$ .
  - Obtained using the maximum likelihood estimation method [1].
  - If  $s_i^k \in \mathcal{R}_{i,n'}^k$ , we estimate that user  $i$ 's position is  $n'$  in the  $k$ -th cycle.

[1] M. A. Youssef, et al, "WLAN location determination via clustering and probability distributions," in Proc. IEEE PerCom, Fort Worth, TX, Mar. 2003.

# Implementation

## Metasurface module:

- Metasurface layer
  - Size:  $69 \times 69 \times 0.52 \text{ cm}^3$
  - 4 phase shifts (interval  $\frac{\pi}{2}$ )
- Control layer
- Power Supply Layer

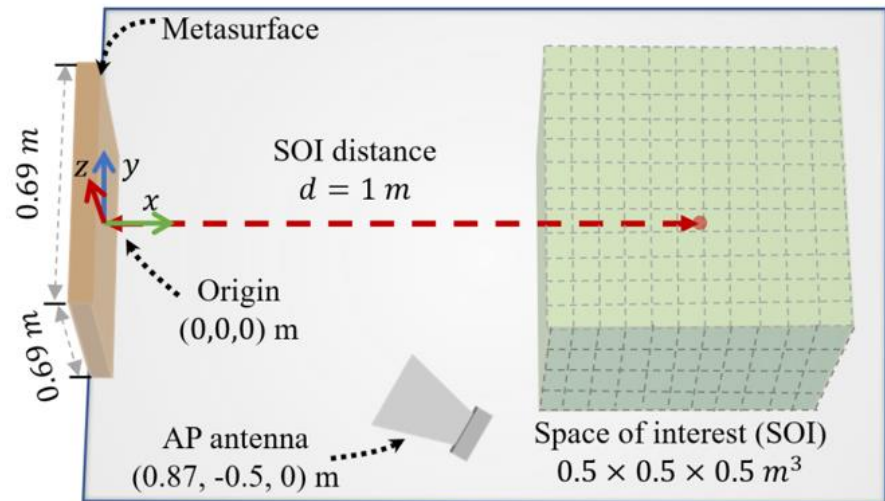


## AP and user modules:

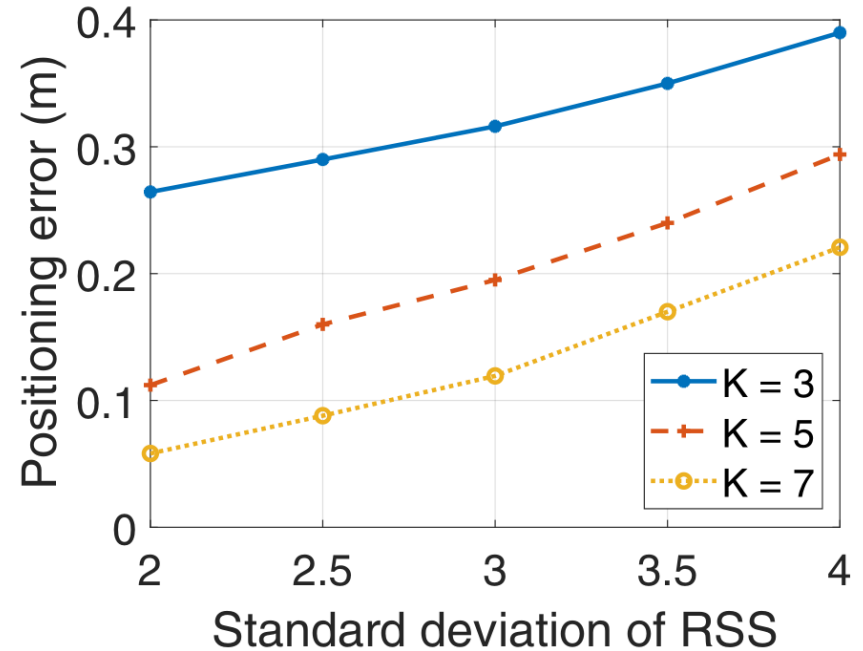
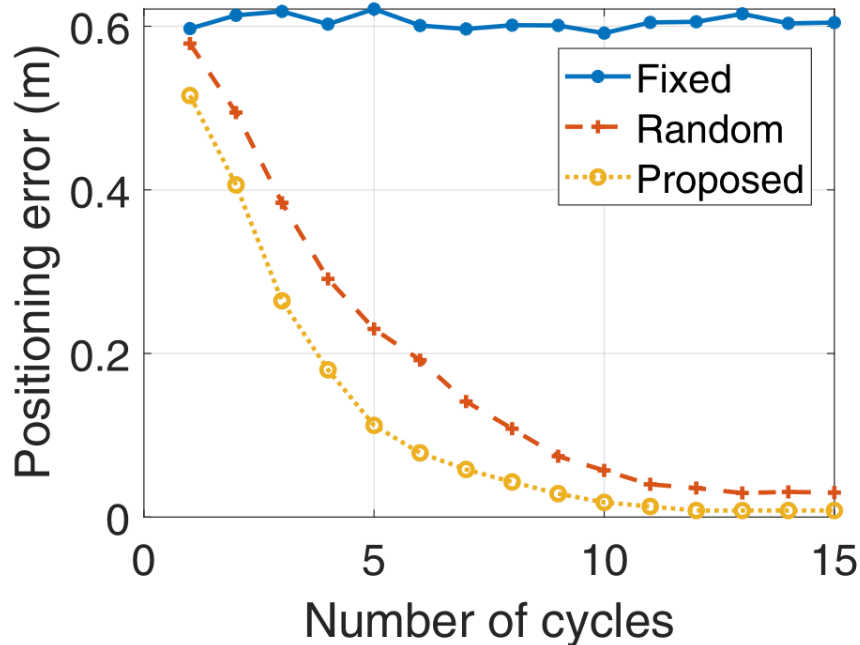
- USRPs (LW-N210)
- Horn antenna (for AP) or small polymer antenna (for users)

## Space of interest (SOI)

- Size:  $0.5 \times 0.5 \times 0.5 \text{ m}^3$



# Simulation Results



- The positioning error obtained by the proposed scheme is much lower and has a faster convergence speed than that of the random configuration scheme.
- The positioning error increases when the standard deviation increases and number of cycles  $K$  decreases.

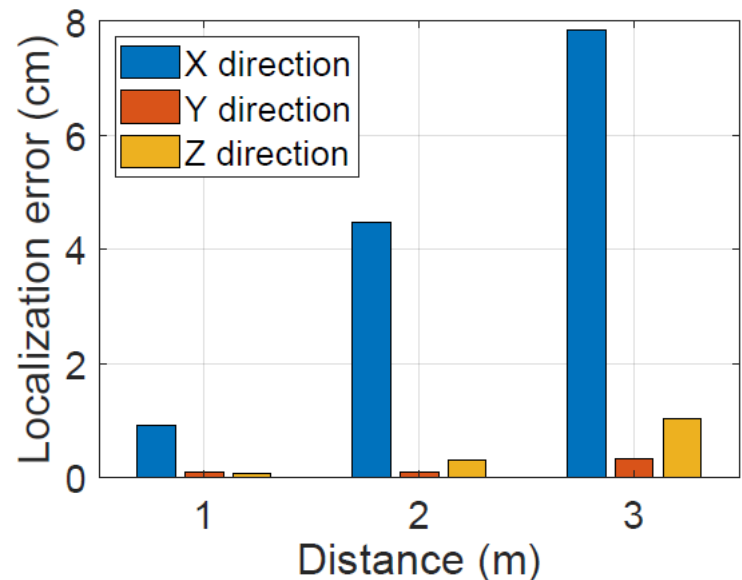
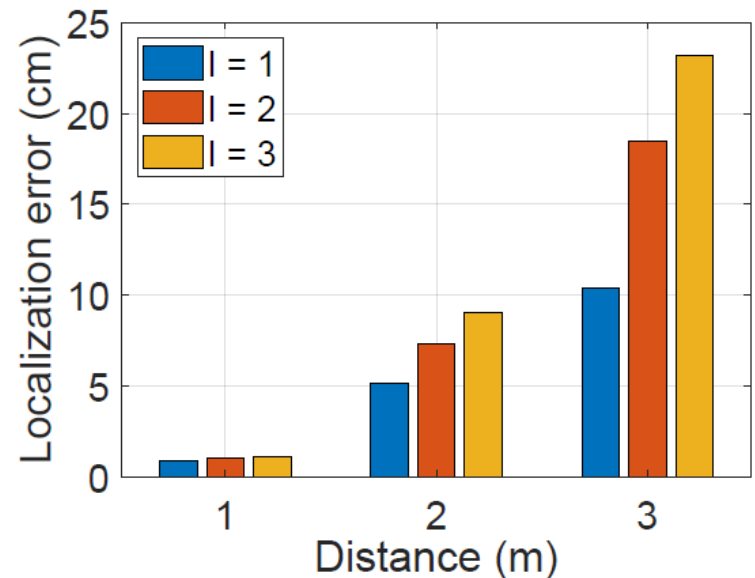
# Experimental Results

## Multi-user localization:

- The localization error increases with the number of users and the SOI distance.

## Accuracy in different axes:

- The localization error in the **x axis** is clearly **larger** than those in the **y and z axes**.
- This is because the **signal correlation in the x axis** (perpendicular to the metamaterials) is higher, rendering it more difficult to distinguish different blocks in the x axis.



# Potential Directions

## Spectrum efficiency

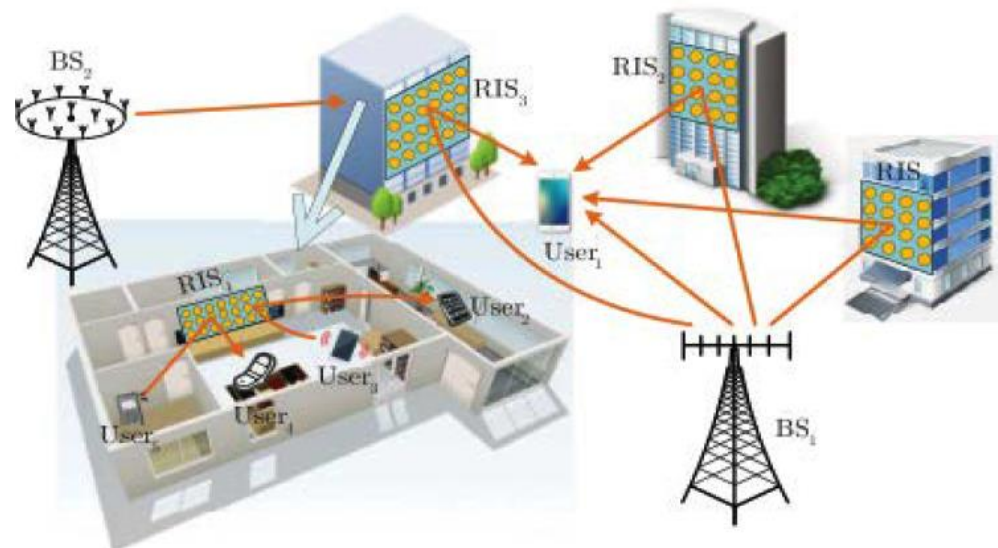
- Broadband Communications: OFDMA
- Full Spectrum Band Operation: mmWave, Terahertz
- Full Dimension Coverage: Transmissive-reflective meta-surface
- Implementation: Real-time environment configuration

## High-resolution sensing

- Mobility and Doppler resolution
- Angular resolution and non-uniform illumination

## Other issues

- Context-awareness
- Security and privacy





# Conclusions

- RIS is a promising solution for 6G providing an **intelligent paradigm** to shape the environments
  - Improve spectrum efficiency and network capacity
  - Extend the coverage and serve cell-edge users
  - Integrate imaging, sensing, and wireless communications
- We explore different aspects related to RIS-aided communications, sensing, and positioning
  - Limited phase shift effect and size effect
  - RIS orientation and placement for coverage extension
  - Hybrid beamforming and intelligent omni surface
  - RF sensing for various applications
  - Ubiquitous positioning

# Publications (1)

## RIS aided Cellular Communications

1. B. Di, H. Zhang, L. Song, Y. Li, Z. Han, and H. V. Poor, “Hybrid Beamforming for Reconfigurable Intelligent Surface based Multi-user Communications: Achievable Rates with Limited Discrete Phase Shifts”, IEEE J. Sel. Areas Commun., vol. 38, no. 8, pp. 1809-1822, Aug. 2020.
2. H. Zhang, B. Di, L. Song, and Z. Han, “Reconfigurable Intelligent Surfaces assisted Communications with Limited Phase Shifts: How Many Phase Shifts Are Enough?” IEEE Trans. Veh. Technol., vol. 69, no. 4, pp. 4498-4502, Apr. 2020.
3. B. Di, H. Zhang, L. Li, L. Song, Y. Li, and Z. Han, “Practical Hybrid Beamforming with Limited-Resolution Phase Shifters for Reconfigurable Intelligent Surface based Multi-user Communications”, IEEE Trans. Veh. Technol., vol. 69, no. 4, pp. 4565-4570, Apr. 2020.
4. M. A. ElMossallamy, H. Zhang, L. Song, K. Seddik, Z. Han, and G. Y. Li, “Reconfigurable Intelligent Surfaces for Wireless Communications: Principles, Challenges, and Opportunities,” IEEE Trans. Cognitive Commun. Netw., vol. 6, no. 3, pp. 990-1002, Sep. 2020.
5. S. Zeng, H. Zhang, B. Di, Z. Han, and L. Song, “Reconfigurable Intelligent Surface (RIS) Assisted Wireless Coverage Extension: RIS Orientation and Location Optimization,” IEEE Commun. Lett., vol. 25, no. 1, pp. 269-273, Jan. 2021.
6. Y. Chen, B. Ai, H. Zhang, Y. Niu, L. Song, Z. Han, and H. V. Poor, “Reconfigurable Intelligent Surface Assisted Device-to-Device Communications,” IEEE Trans. Wireless Commun., to appear. Arxiv: <https://arxiv.org/abs/2007.00859>.
7. X. Cao, B. Yang, H. Zhang, C. Yuen, and Z. Han, “Reconfigurable Intelligent Surfaces Assisted MAC for 6G: Protocol Design, Analysis and Optimization,” IEEE Internet Things J., under revision.
8. M. ElMossallamy, H. Zhang, R. Sultan, K. Seddik, L. Song, G. Y. Li, and Z. Han, “On Spatial Multiplexing Using Reconfigurable Intelligent Surfaces,” IEEE Wireless Commun. Lett., to appear.

# Publications (2)

## RIS aided Cellular Communications

9. H. Zhang, B. Di, Z. Han, H. V. Poor, and L. Song, “Reconfigurable Intelligent Surface assisted Multi-user Communications: How Many Reflective Elements Do We Need?” IEEE Wireless Commun. Lett., under revision.
10. Y. Zhang, B. Di, H. Zhang, J. Lin, Y. Li, and L. Song, “Reconfigurable Intelligent Surface Aided Cell-free Massive MIMO Communications,” IEEE Wireless Commun. Lett., to appear.
11. S. Zhang, H. Zhang, B. Di, Y. Tan, Z. Han, and L. Song, “Reflective-Transmissive Metasurface Aided Communications for Full-dimensional Coverage Extension,” IEEE Trans. Veh. Technol., IEEE Trans. Veh. Technol., vol. 69, no. 11, pp. 13905-13909, Nov. 2020.
12. M. ElMossallamy, H. Zhang, R. Sultan, K. Seddik, L. Song, G. Y. Li, and Z. Han, “On Spatial Multiplexing Using Reconfigurable Intelligent Surfaces,” IEEE Wireless Commun. Lett., to appear.
13. S. Zhang, H. Zhang, B. Di, Y. Tan, M. D. Renzo, Z. Han, H. V. Poor, and L. Song, “Intelligent Omni-Surface: Ubiquitous Wireless Transmission by Reflective-Transmissive Metasurfaces,” IEEE Trans. Wireless Commun., submitted. Arxiv: <https://arxiv.org/abs/2011.00765>.
14. Y. Zhang, B. Di, H. Zhang, J. Lin, Y. Li, and L. Song, “Beyond Cell-free MIMO: Energy Efficient Reconfigurable Intelligent Surface Aided Cell-free MIMO Communications,” IEEE Trans. Cognitive Commun. Netw., to appear.
15. H. Zhang, S. Zeng, B. Di, Y. Tan, M. D. Renzo, M. Debbah, L. Song, Z. Han, and H. V. Poor, “Intelligent Reflective-Transmissive Metasurfaces for Full-Dimensional Communications: Principles, Technologies, and Implementation,” IEEE Commun. Mag., submitted.

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## **RIS aided Cellular Communications**

16. E. Shtaiwi, H. Zhang, M. Youssef, A. Abdelhadi, and Z. Han, "Channel Estimation Approach for RIS Assisted MIMO Systems," *IEEE Trans. Cognitive Commun. Netw.*, under revision.
17. R. Deng, B. Di, H. Zhang, Y. Tan, and L. Song, "Reconfigurable Holographic Surface: Holographic Beamforming for Metasurface-aided Wireless Communications," *IEEE Trans. Veh. Technol.*, submitted.
18. S. Zeng, H. Zhang, B. Di, Y. Tan, Z. Han, H. V. Poor, and L. Song, "Reconfigurable Intelligent Surfaces in 6G: Reflective, Transmissive, or Both?," *IEEE Commun. Lett.*, under revision.
19. H. Zhang, L. Song, Z. Han, and H. V. Poor, "Spatial Equalization Before Reception: Reconfigurable Intelligent Surfaces for Multi-Path Mitigation," in *Proc. IEEE ICASSP*, Toronto, Canada, Jun. 2021.
20. X. Cao, B. Yang, H. Zhang, L. Qian, C. Yuen, and Z. Han, "Reconfigurable Intelligent Surface Assisted Internet-of-Things: MAC Design and Optimization," in *Proc. IEEE WCNC Workshops*, Nanjing, China, Mar. 2021.
21. E. Shtaiwi, H. Zhang, A. Abdelhadi, and Z. Han, "RIS-Assisted mmWave Channel Estimation Using Convolutional Neural Networks," in *Proc. IEEE WCNC Workshops*, Nanjing, China, Mar. 2021.
22. Y. Chen, B. Ai, H. Zhang, Y. Niu, L. Song, Z. Han, and H. V. Poor, "Reconfigurable Intelligent Surface Assisted D2D Networks: Power and Discrete Phase Shift Design," in *Proc. IEEE GLOBECOM*, Taipei, Taiwan, Dec. 2020.

# Publications (4)

## RIS aided RF Sensing

1. J. Hu, H. Zhang, B. Di, L. Li, L. Song, Y. Li, Z. Han, and H. V. Poor, "Reconfigurable Intelligent Surfaces based RF Sensing: Design, Optimization, and Implementation," IEEE J. Sel. Areas Commun., vol. 38, no. 11, pp. 2700-2716, Nov. 2020.
2. J. Hu, H. Zhang, K. Bian, M. D. Renzo, Z. Han, and L. Song, "MetaSensing: Intelligent Metasurface Assisted RF 3D Sensing by Deep Reinforcement Learning," , IEEE J. Sel. Areas Commun., under review.
3. H. Zhang, H. Zhang, B. Di, K. Bian, Z. Han, and L. Song, "Towards Ubiquitous Positioning by Leveraging Reconfigurable Intelligent Surface," IEEE Commun. vol. 25, no. 1, pp. 284-288, Jan. 2021.
4. H. Zhang, J. Hu, H. Zhang, B. Di, K. Bian, Z. Han, and L. Song, "MetaRadar: Indoor Localization by Reconfigurable Metamaterials," IEEE Trans. Mobile Comput., to appear. Arxiv: <https://arxiv.org/abs/2008.02459>.
5. J. Hu, H. Zhang, K. Bian, Z. Han, H. V. Poor, and L. Song, "HoloSketch: Semantic Segmentation by Radio Environment Reconfiguration," IEEE Trans. Mobile Comput., submitted.
6. H. Zhang, H. Zhang, B. Di, K. Bian, Z. Han, and L. Song, "MetaLocalization: Reconfigurable Intelligent Surface Aided Multi-user Wireless Indoor Localization," IEEE Trans. Wireless Commun., under revision.

# Thanks for your attending

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