MetaSensing: Reconfigurable Intelligent Surface Assisted RF Sensing and Localization

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

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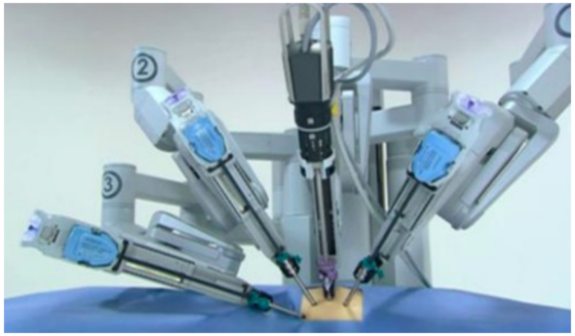
Moving Towards 6G: Emerging Use Cases

VR/AR

AR for surgery

VR for education

Internet-of-Things



Auto-manufacturing

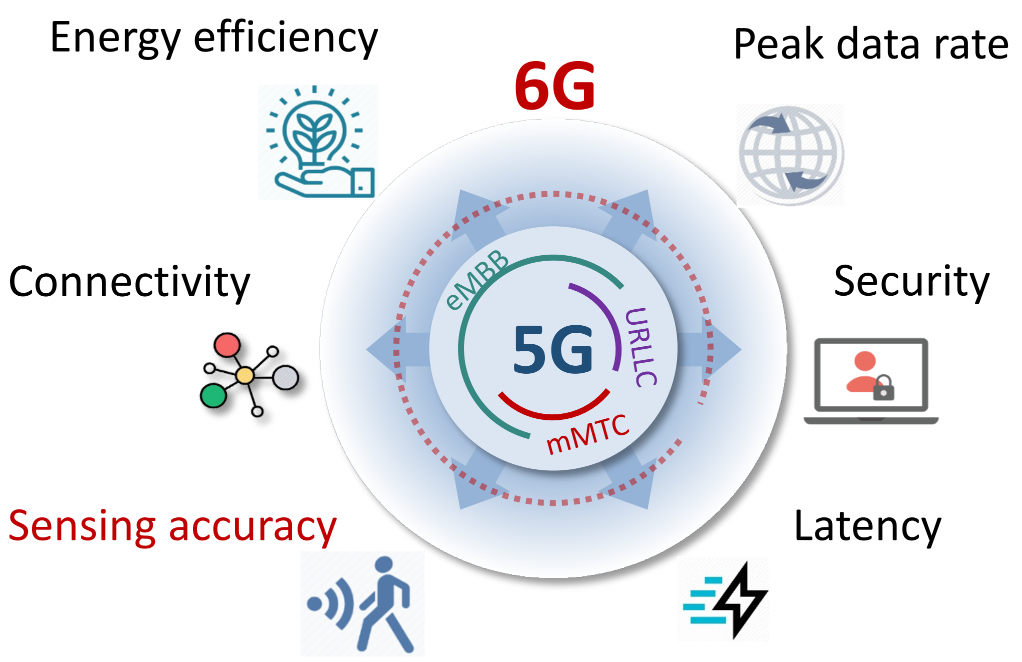
E-health

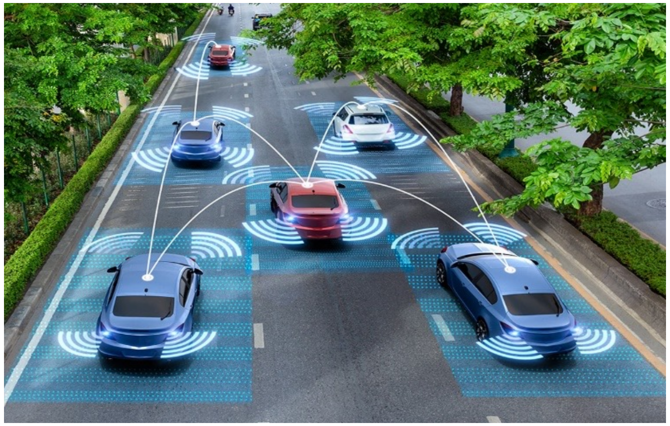
Intelligence

Smart home

Environment sensing

General 6G KPI Targets





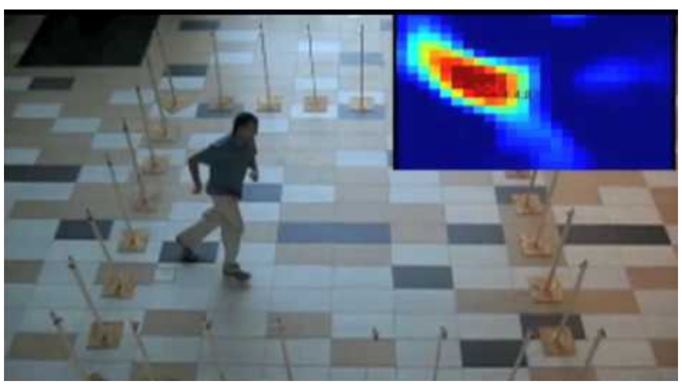
Greater sensing capability

Higher positioning accuracy

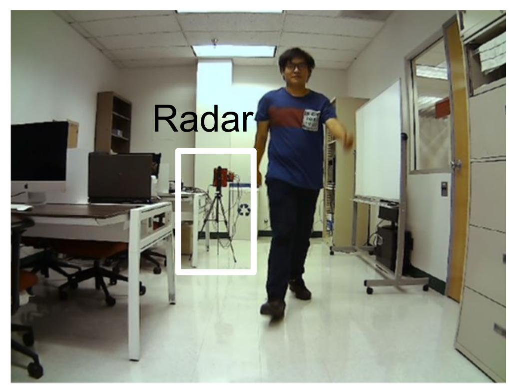
6G Challenges: Sensing Efficiency

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



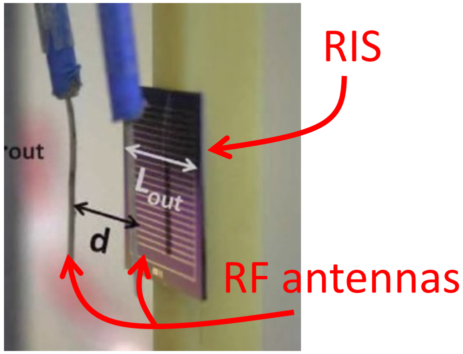
mmWave Radar

Solutions: Meta-Material aided Sensing

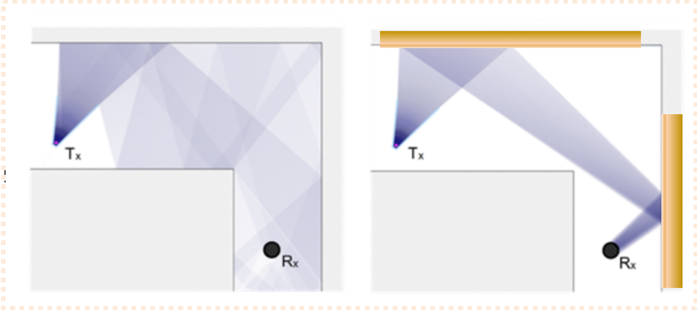
Expectation on a new technology

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

Reconfigurable Meta-surfaces



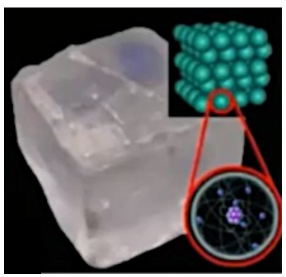
- Implemented by metamaterial
- Cost efficient in manufacture and deployment
- Control and customize favorable radio environments
- Provide high accuracy contact/contactless sensing with wireless data gathering
- So-called Reconfigurable Intelligent Surface (RIS) or Intelligent Reflecting Surface (IRS)



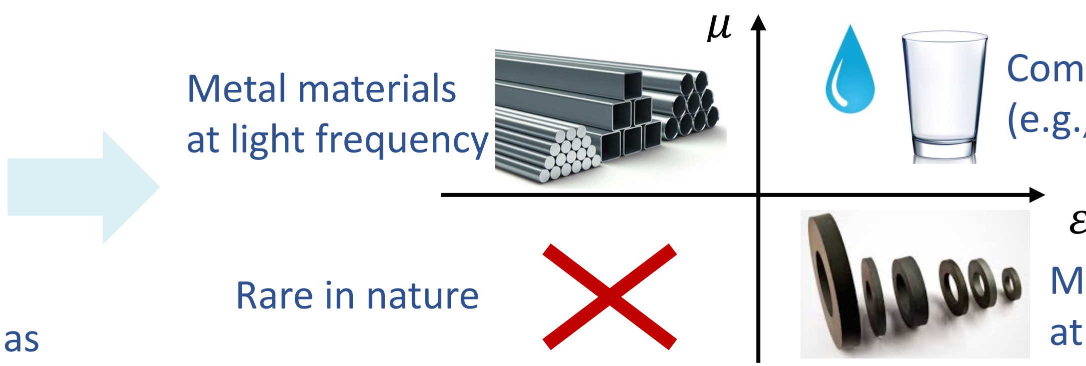
Introduction of Metamaterial

Natural Materials : Limited EM Wave Control Capability

- The *dielectric permittivity,* ε, and *magnetic conductivity,* μ, 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 ε and μ, and thus limited capability to control EM waves



Atom arrangement has limited possibilities



Metamaterials: Powerful EM Wave Control Capability

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

History of Metamaterial Development

1968

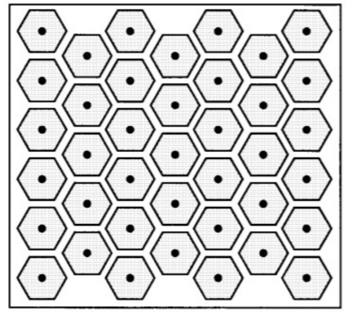
Veselago. Concept of Left-handed material

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

1996 & 1999

Pendry. Realize -ε and -μ

- -ε: periodic array of metallic rods
- -μ: periodic array of split ring



1999

Sievenpiper. Proposal of meta-surface

- Two-dimensional
- Simplify design and manufacturing

2001

D. R. Smith. Experimental verification

- Left-handed material

2001

Sievenpiper.
Programmable metasurface

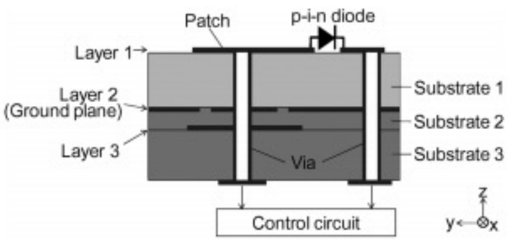
- Varactor
- 360^o reflection phase tuning

2006

Pendry, et al.
Transformation optics

- Design metamaterial with any ϵ and μ
- Enabling flexible control of EM wave

History of Metamaterial Development

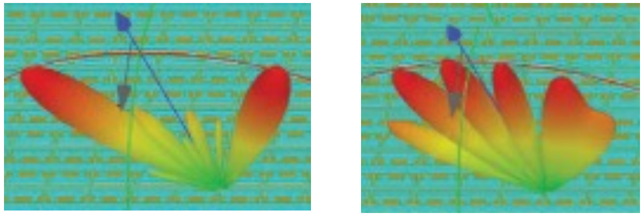


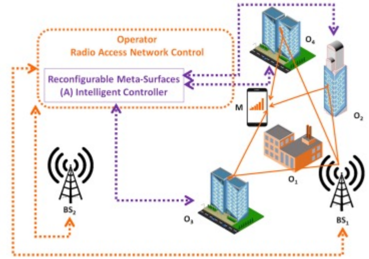
H. Kamoda, et al.
Reconfigurable large reflectarray with PIN diodes
- Easy to control
- Millimeter wave

2011

2014

T. Cui, et al. Programmable metasurface with PIN diodes
- Simplify the design
- Digital coding



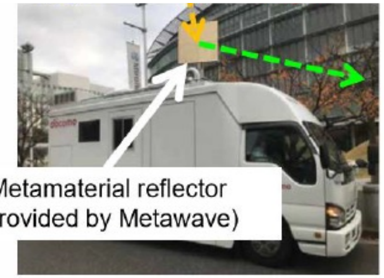


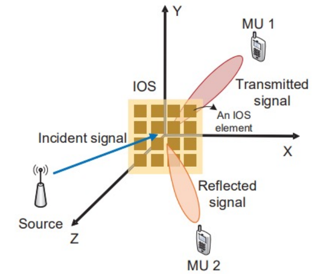
M. D. Renzo, et al.
Proposal of reconfigurable intelligent surfaces
- Focus on reflection
- Extensive applications in wireless networks

2019

2019

NTT Docomo.
Protype of metamaterial reflector
- 10x increase in data rate


Metamaterial reflector
(provided by Metawave)



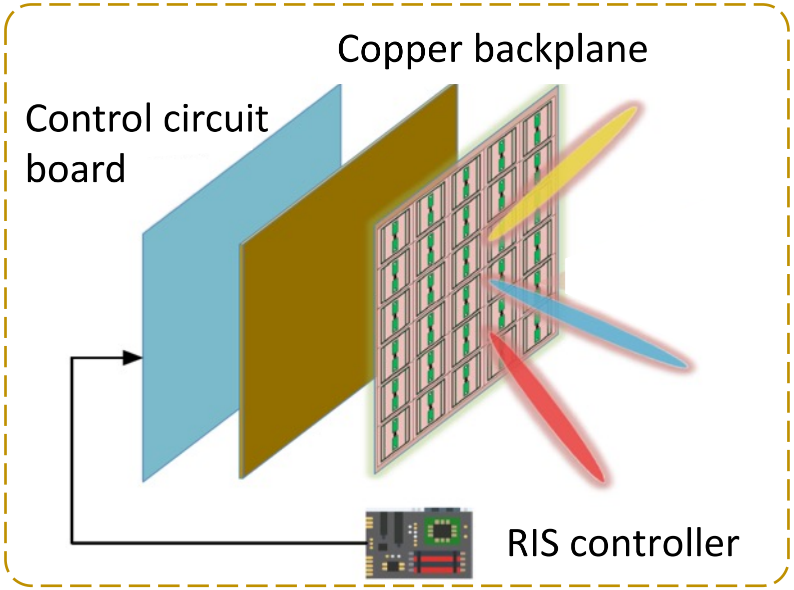
S. Zhang, et al.
Proposal of intelligent omni-surface
- Enabling dual function of reflection and transmission

2020

Reconfigurable Intelligent Surfaces (RIS)

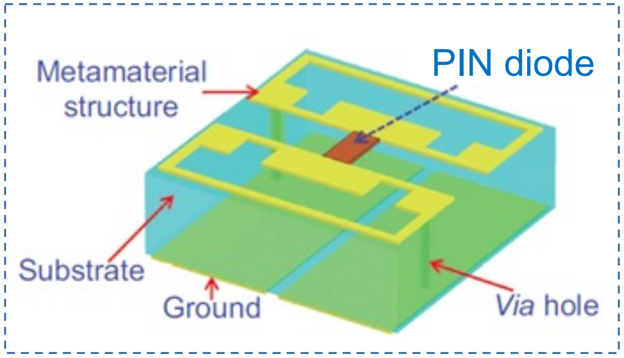
An ultra-thin metasurface composed of multiple layers

- **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 controablle phase shift
- Working frequency: from sub-6 GHz to THz



Example of a programmable metamaterial particle

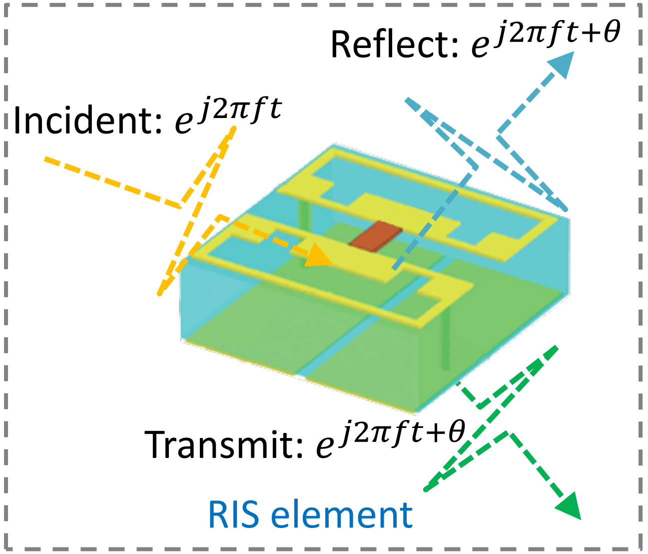
Working Principle for Wireless Communications

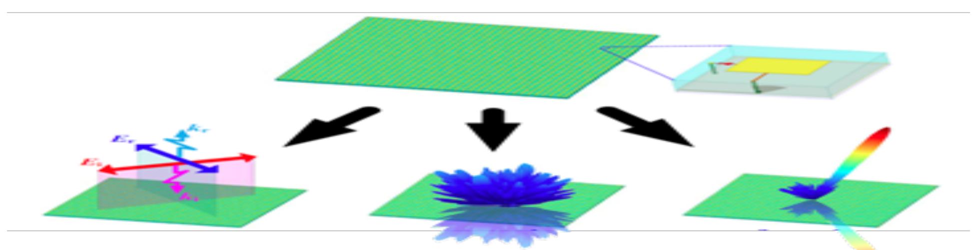
RIS works as a beamformer

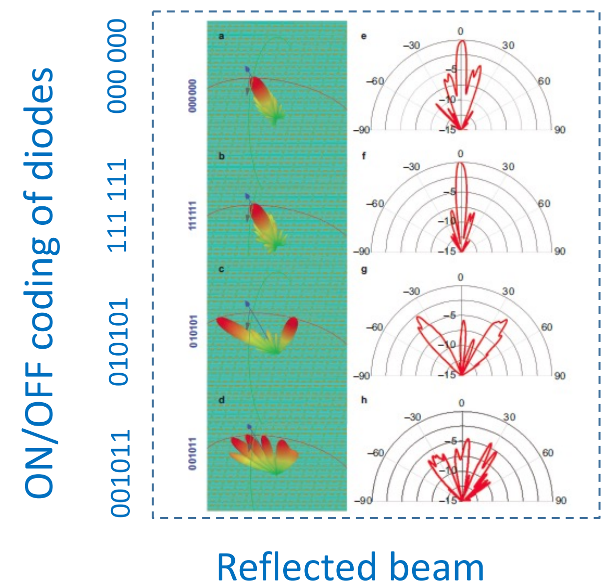
- Signals can be reflected or transmitted
- Phase shift of the radiation is controlled by PIN diodes' bias voltages (ON/OFF of the diode)
- Programming the ON/OFF of all diodes collectively realize different beamforming modes

Advantage

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





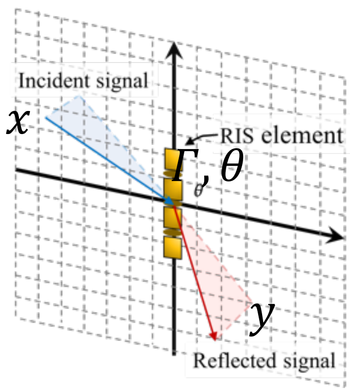


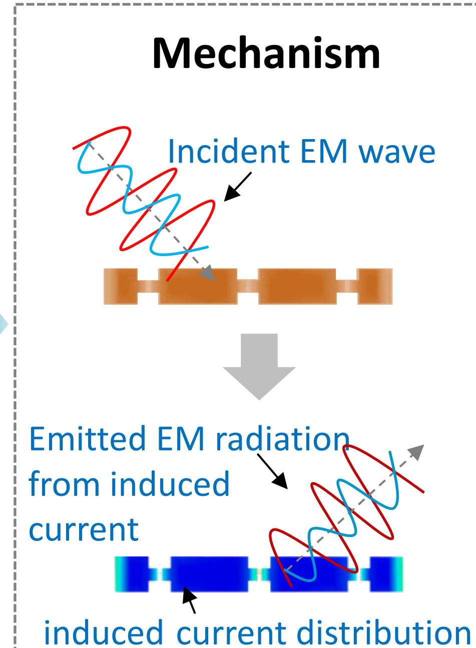
Signal Reflection Model

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 $\Longrightarrow 2^K$ phase shifts).
- The parameters of an RIS element[1] are carefully designed so that the phase shifts have uniform intervals.

[1]: e.g., shape of the metal patch and type of the PIN diodes

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.

Channel Model

Rician Model

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

$$\tilde{h}_{m,n} = \sqrt{\frac{\kappa}{\kappa+1}}\,\boxed{h_{m,n}} + \sqrt{\frac{1}{\kappa+1}}\,\boxed{\hat{h}_{m,n}}$$

Ratio of LoS to NLoS LoS NLoS

- Product of distance path loss

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

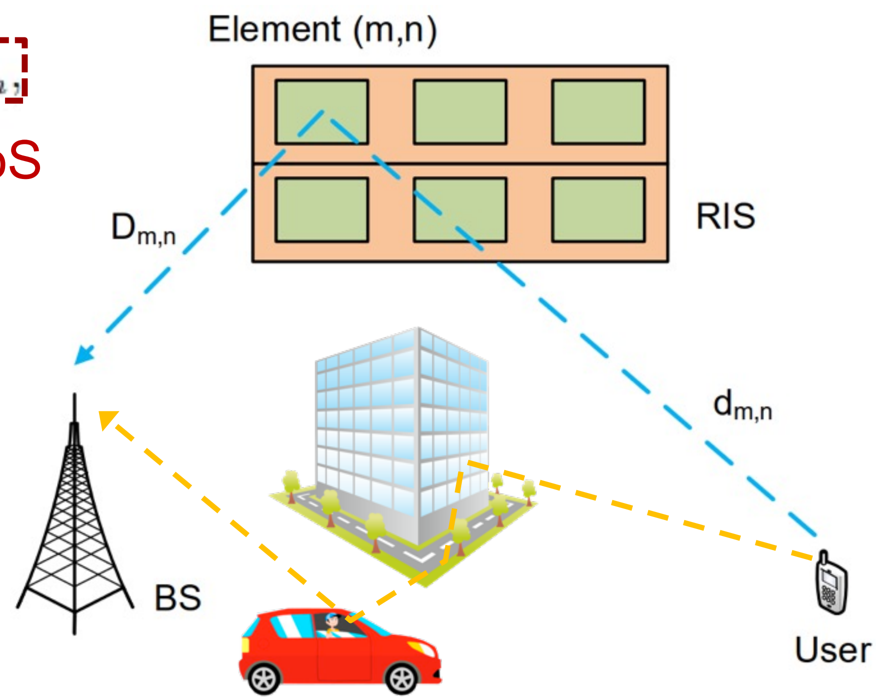
$$|\tilde{h}_{m,n}|^2 \propto d_{m,n}^{-\alpha} D_{m,n}^{-\alpha}$$

- Received signal

noise

$$y = \sum_{m,n} \Gamma e^{j\theta_{m,n}} \tilde{h}_{m,n} x + w$$

Reflection coefficient Channel gain



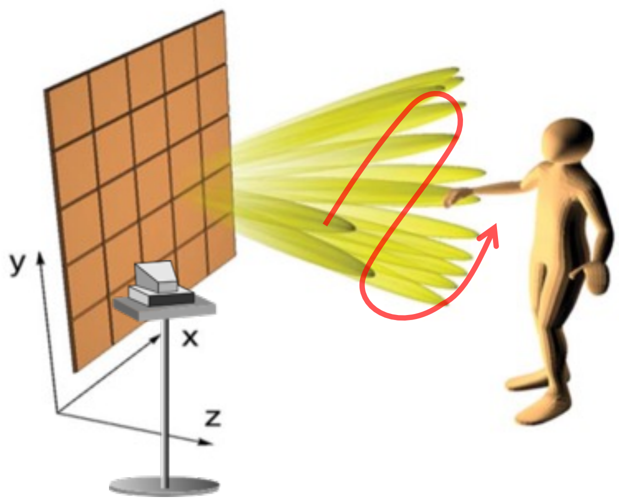
$h_{m,n}$, LoS component

$\hat{h}_{m,n}$, NLoS component

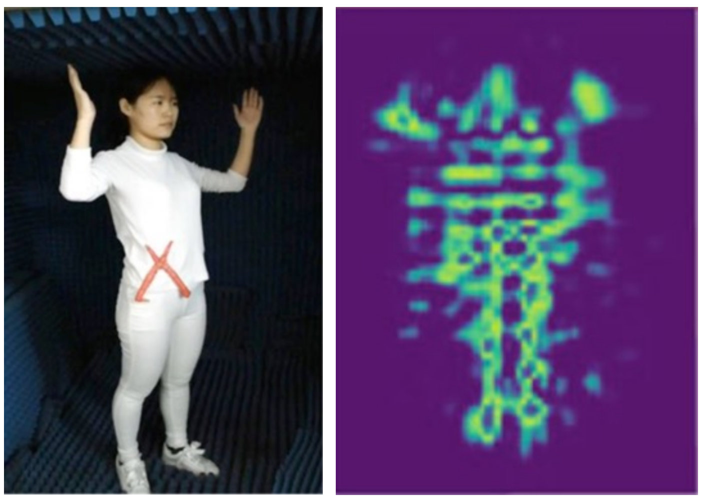
Applications: Radio Frequency Sensing

Indoor Localization and Recognition

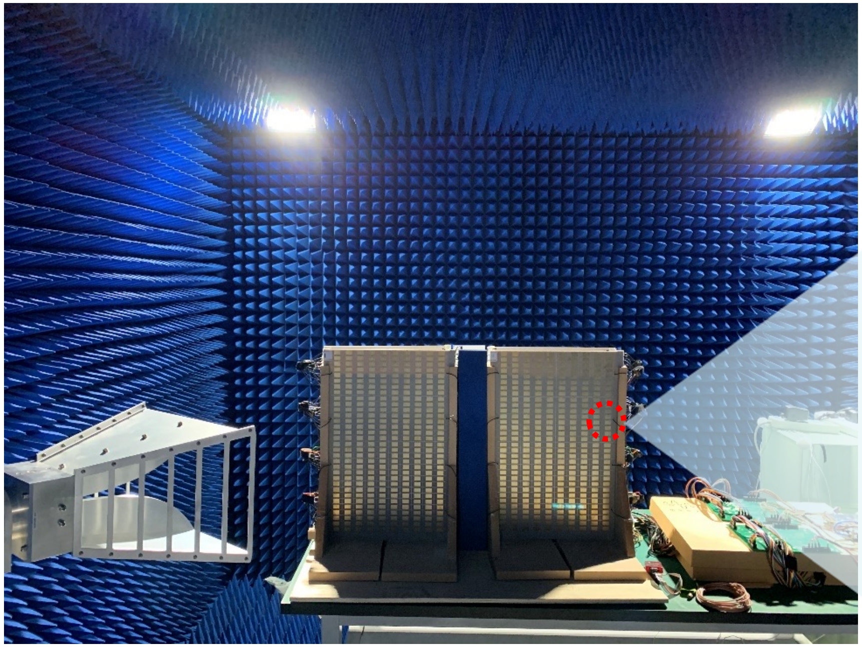
- Enhance remote RF sensing by customize radio environments.
- Enable high accuracy indoor human and object localization and recognition

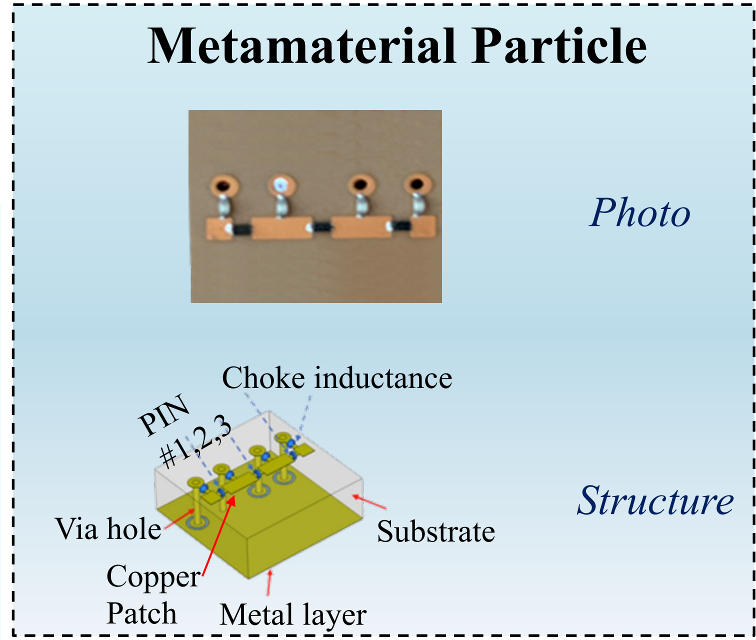


Customize signal beams for scanning human location


Customized radio environement for sensing human posture

Prototype of Metasurface





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

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

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  - Case 3: Ubiquitous Localization
- **Potential Future Directions**
- **Conclusions**

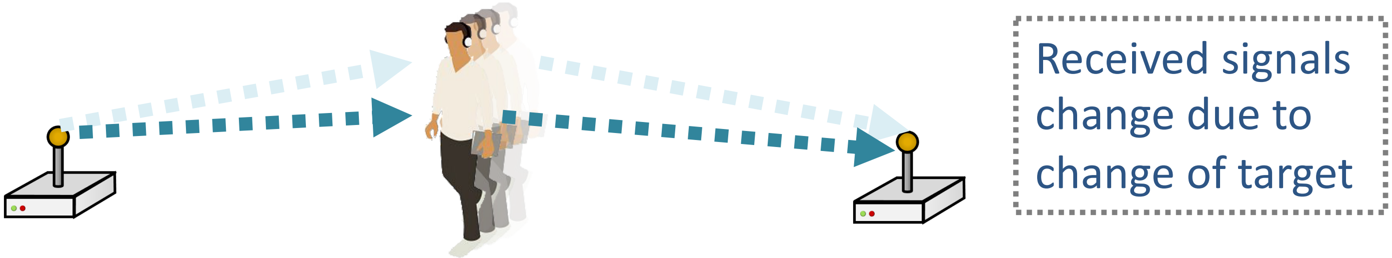
Background

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 I: RIS aided Posture Recognition

RIS-based RF Posture 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 does RIS control the wireless environment*
  - The discrete phase shifts of a massive number of RIS elements need to be determined.
- Decision function design: *How does Rx judge human posture*
  - RF channels involve an RIS and a practical are hard to analyze, which makes the relationship between Rx signals and human posture inexplicit.
- Moreover, RIS configuration and decision function are coupled.

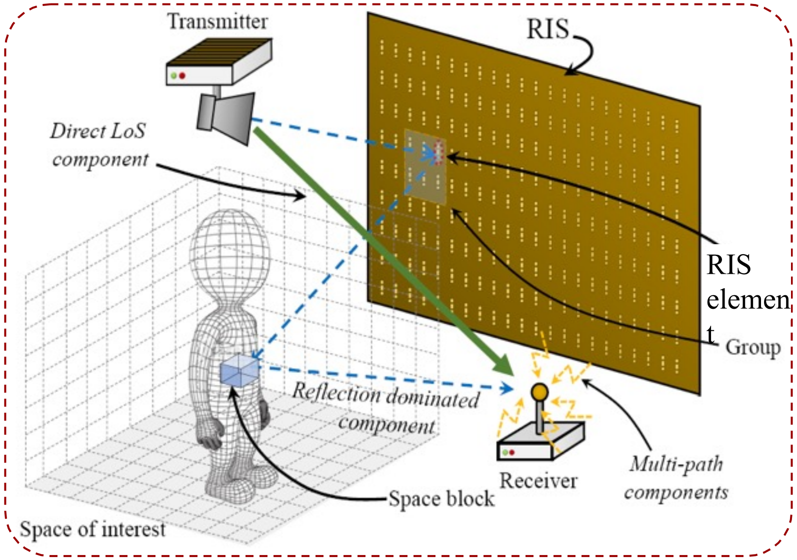
Model Description

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

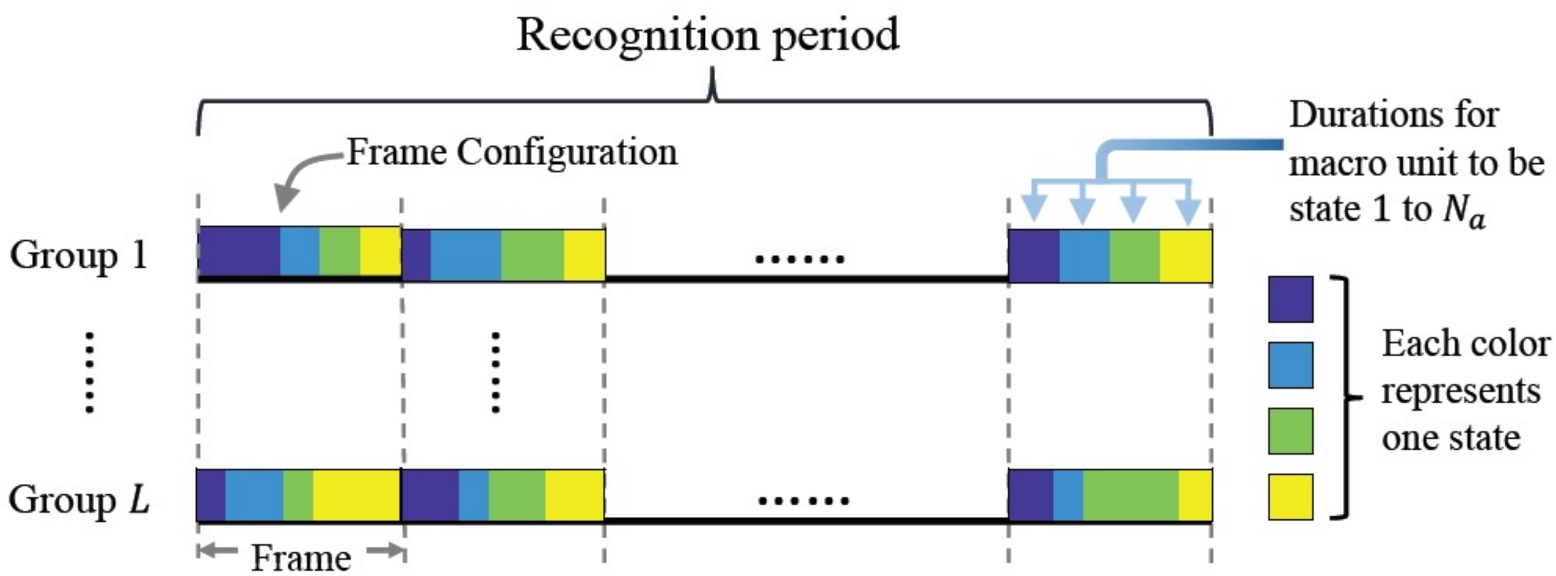
Recognition Period:

- 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 use the decision function to generate the probabilities for deciding on different human postures.

Optimization Problem: Minimize the false recognition cost (Bayesian)

$$\text{(P1)}\quad \min_{\boldsymbol{T},\boldsymbol{\mathcal{L}}} C_{FR}(\boldsymbol{T},\boldsymbol{\mathcal{L}}) = \sum_{i,i'} \underbrace{\Pr(\mathrm{pos}_i)}_{} \cdot \underbrace{cost(i,i')}_{} \cdot \mathbb{E}_{\boldsymbol{y}}[\underbrace{\Pr(\boldsymbol{y}|\mathrm{pos}_i)}_{} \cdot \underbrace{\mathcal{L}_{i'}(\boldsymbol{y})}_{}]$$

Optimization Variables
$\boldsymbol{T}$: Frame configurations in a recognition period
$\boldsymbol{\mathcal{L}}$: Decision function

Probability of Posture i to appear

Cost for recognizing Posture i as i'

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

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

Problem Decomposition:

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

$C_{FR}(\boldsymbol{T},\boldsymbol{\mathcal{L}})$ → $C_{FR}(\boldsymbol{T})$, $C_{FR}(\boldsymbol{\mathcal{L}})$

Coupled optimization objective in (P1)

$C_{FR}(\boldsymbol{T})$: *RIS frame configuration optimization objective*

$C_{FR}(\boldsymbol{\mathcal{L}})$: *Decision function optimization objective*

Algorithm Design: Optimize $\mathbf{T}$

Solving Frame Configuration Optimization:

- **Step 1:** Construct measurement matrix $\boldsymbol{\Gamma}$ given frame configuration
  - Element $(\boldsymbol{\Gamma})_{k,j}$ is the received signals in the k-th frame due to unit reflection coefficient in the j-th space block, i.e.,

$$(\boldsymbol{\Gamma})_{k,j} = \boldsymbol{t}_k \boldsymbol{\alpha}_j$$

$\boldsymbol{t}_k$: k-th row of frame configuration $\boldsymbol{T}$

$\boldsymbol{\alpha}_j$: channels for the j-th block given RIS elements in N_a states

  - Based on compressive sensing technique, minimizing mutual coherence of $\boldsymbol{\Gamma}$ increases the information of space reflection involved in received signals.

- **Step 2:** Minimize mutual coherence of $\boldsymbol{\Gamma}$ w.r.t. $\boldsymbol{T}$, i.e.,

$$(SP1)\ \min_{\boldsymbol{T}}\ \mu(\boldsymbol{\Gamma}) = \sum_{j \neq j'} \frac{|\boldsymbol{\gamma}_j^H \boldsymbol{\gamma}_{j'}|}{\| \boldsymbol{\gamma}_j \| \cdot \| \boldsymbol{\gamma}_{j'} \|}.$$

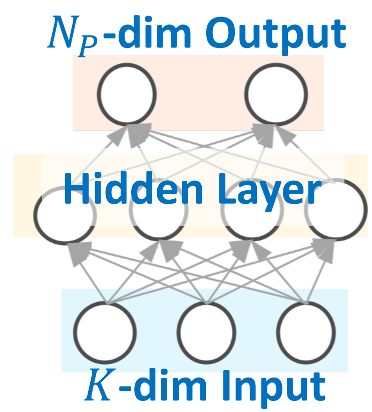
$\boldsymbol{\gamma}_j$: the received signal vectors for the j-th block under configurations in K frames

- To solve (SP1) efficiently, configurations in K frames are optimized iteratively.
- In each iteration, *pattern search* and *augmented Lagrangian* methods are used to coarsely and finely optimize $\boldsymbol{t}_k$.

Algorithm Design: Optimize L

Solving Decision Function Optimization:

- **Step 1:** Model the decision function $\mathcal{L}$ with a neural network.
  - Input layer: received signals in K frames
  - Output layer: obtain probability of each posture using a softmax function



- **Step 2:** Optimize parameters of the neural network
  - Given the optimized frame configuration $\boldsymbol{T}^*$ in $(SP1)$, a training data set of received signal vectors labeled with different human postures is collected
  - The objective is to minimize the *false recognition cost* by optimizing the weights of the neural network, i.e., $\boldsymbol{\theta}$, by using *back-propagation method*

$$(SP2)\ \min_{\boldsymbol{\theta}} \sum_i \sum_{n \neq l_i} \mathcal{L}_n^{\boldsymbol{\theta}}(\boldsymbol{r}_i).$$

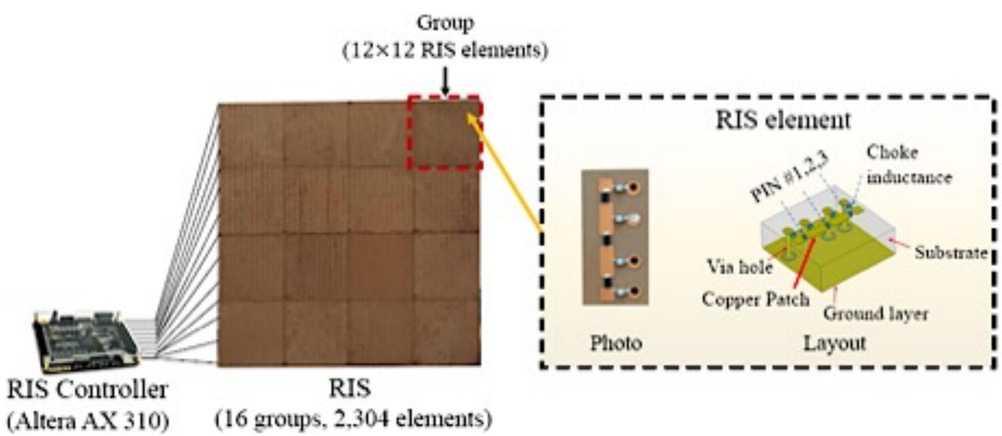
$\boldsymbol{r}_i$: i-th received signal vectors in training data set

l_i: posture label of $\boldsymbol{r}_i$ in the training data set

Implementation

RIS & RIS Control Circuit

- **Size of RIS:** 69 × 69 × 0.52 cm^3
- **Dielectric substrate:** Rogers 3010 (dielectric constant: $\varepsilon = 10.2$)
- **PIN diodes:** BAR 65-02L × 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



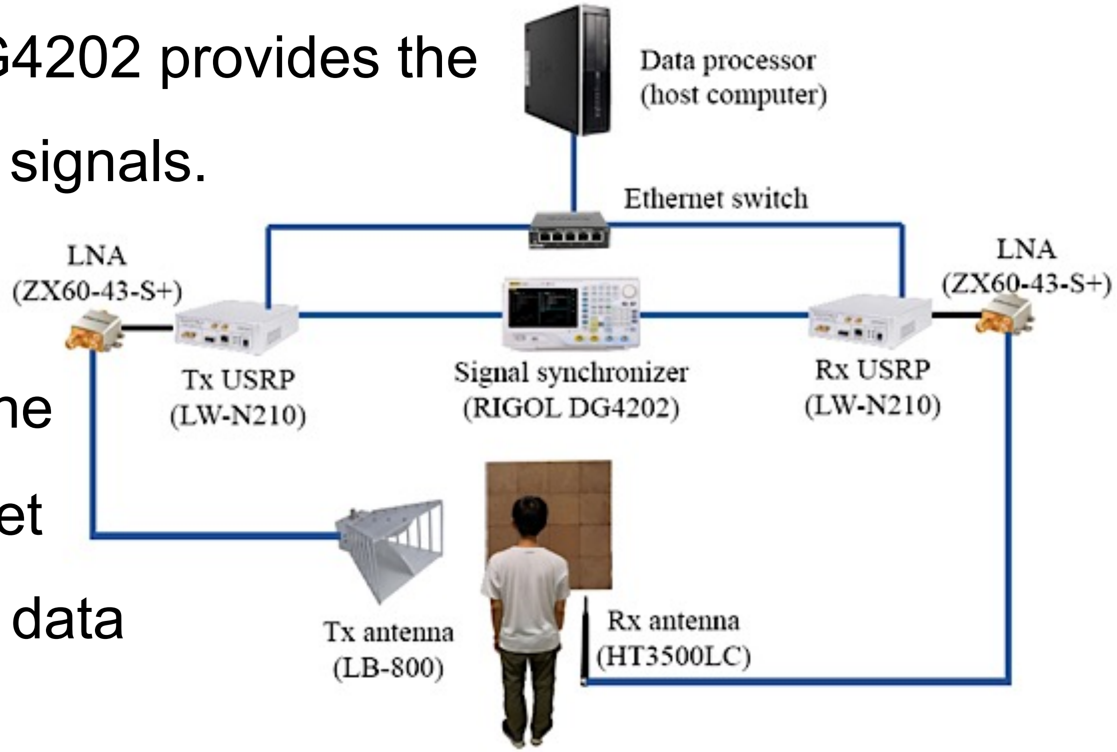
Implementation

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

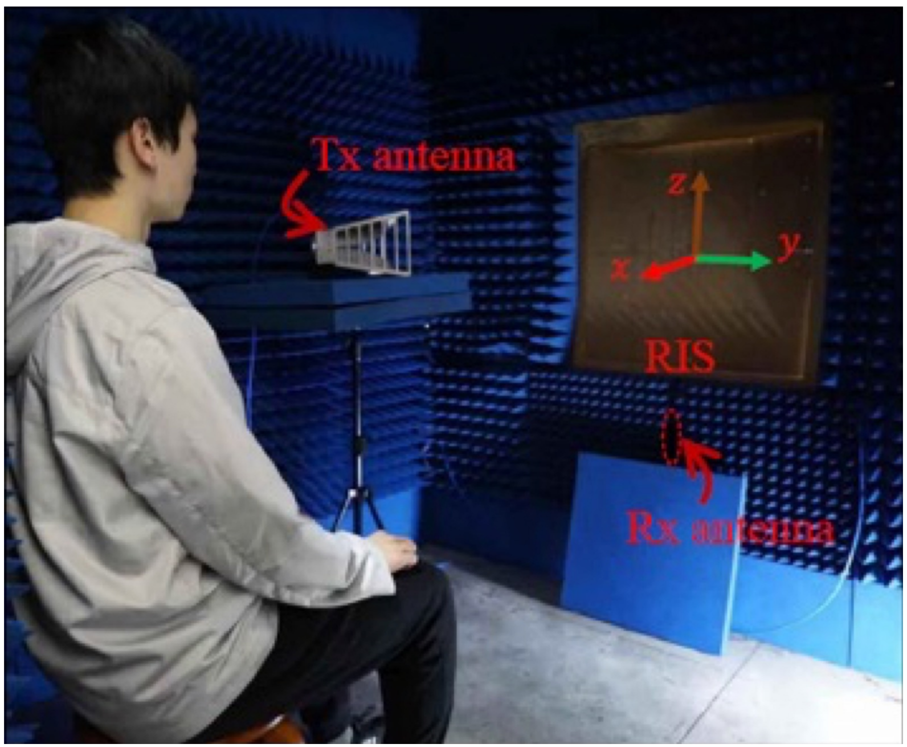
- Host computer connects the Tx/Rx USRPs with Ethernet to send/receive baseband data

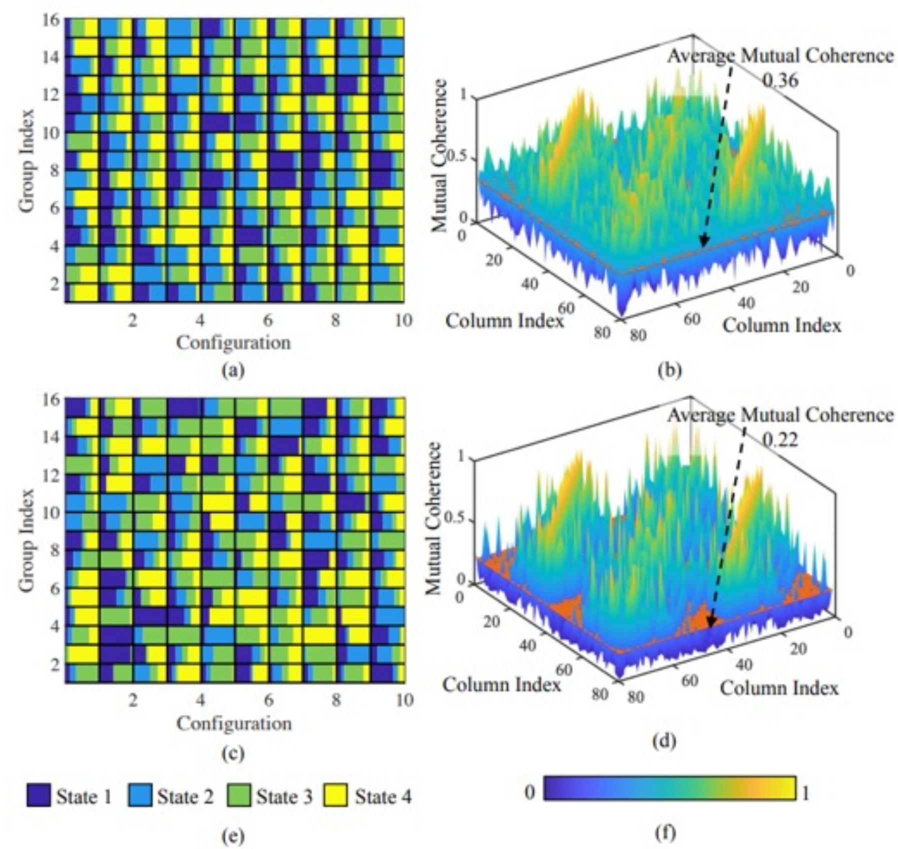


Experimental Results

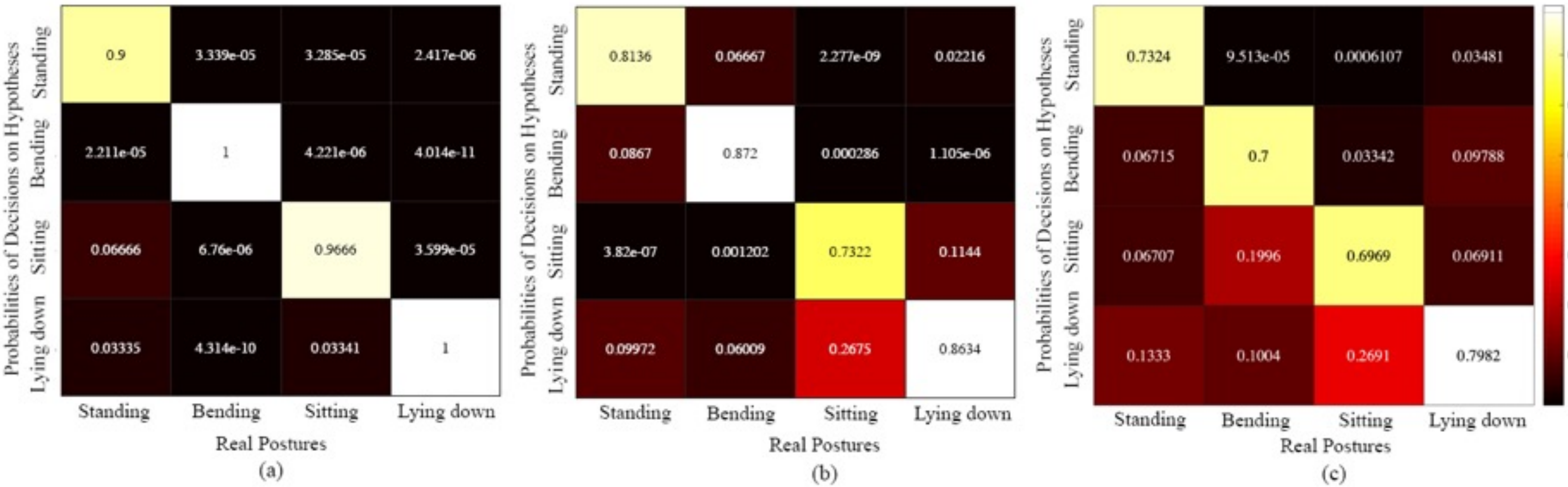
Effectiveness:

- The average mutual coherence of the measurement matrix is reduced (from 0.36 to 0.22), which can improve sensing accuracy.





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 II: RIS aided RF 3D Shape Sensing

MetaSensing:

Intelligent Metasurface Assisted RF 3D Shape 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, to be published.

Motivation

RF 3D shape 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 shape sensing

- RIS controls RF signal beams by manipulating configuration
- Using controlled RF signal beams, 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.

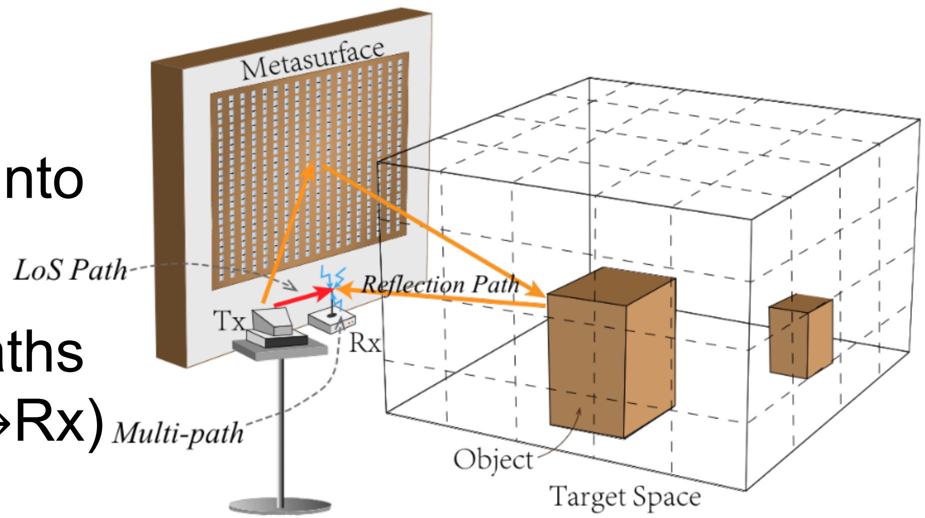
Model Description

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

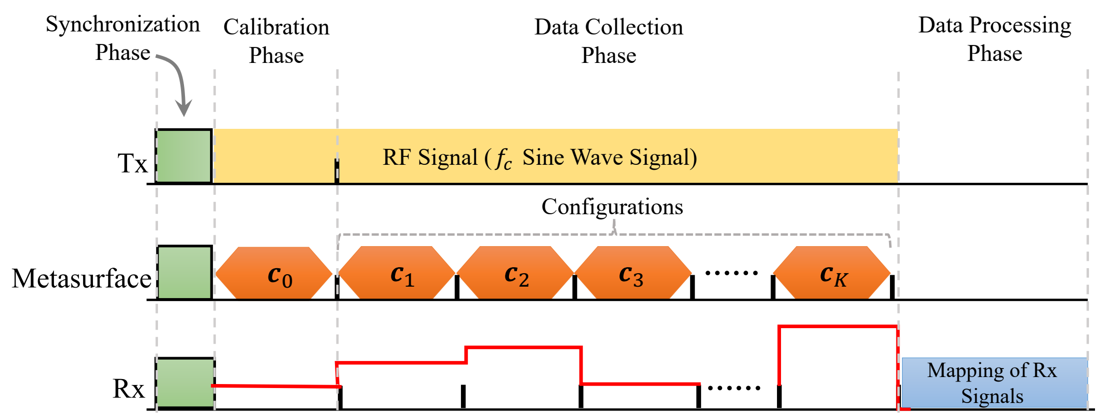
- The target space is discretized into M space grids.
- The total $N \times M$ reflection paths (Tx→ N RIS elements→ M grids→Rx) are summed at the Rx



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 $\boldsymbol{f}^{\boldsymbol{w}}$ to estimate the probabilities for objects to be at M space grids, i.e., $\hat{\boldsymbol{p}} \in [0,1]^M$.

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

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

Entropy of Estimation
p_m: probability of m-th grid being non-empty

$$
\begin{aligned}
\text{(P1)}: \min_{\boldsymbol{C},\boldsymbol{w}} \quad & -\mathbb{E}_{\boldsymbol{p}}\left[\sum_{m=1}^{M} \boxed{p_m \cdot \ln(\hat{p}_m)} + \boxed{(1-p_m)\cdot \ln(1-\hat{p}_m)}\right], \\
s.t. \quad & (\hat{p}_1, ..., \hat{p}_M) = \boldsymbol{f}^{\boldsymbol{w}}(\tilde{\boldsymbol{y}}), \\
& \tilde{\boldsymbol{y}} = \sqrt{P}\cdot x \cdot (\boldsymbol{C} - \boldsymbol{C}_0)\boldsymbol{A} + \tilde{\boldsymbol{\sigma}}, \\
& \begin{cases} \boldsymbol{C} = (\boldsymbol{c}_1^T, ..., \boldsymbol{c}_K^T)^T, \\ \boldsymbol{c}_k = (\hat{\boldsymbol{o}}(c_{k,1}), ..., \hat{\boldsymbol{o}}(c_{k,N})), \ \forall k \in [1, K], \\ c_{k,n} \in [1, N_S], \ \forall k \in [1,K], n \in [1,N]. \end{cases}
\end{aligned}
$$

Constraints

(1) Estimation is obtained by mapping of received signals

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

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

Challenge :

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

Algorithm Design

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

Coupled optimization objective in (P1)

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

RIS configuration optimization (sP1)

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

Challenge: Configuration matrix $\boldsymbol{C}$ 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 $\boldsymbol{C}$.

Mapping function optimization (sP2)

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

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

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

Algorithm Design

Updating RIS configuration selection policy $\boldsymbol{\pi}$

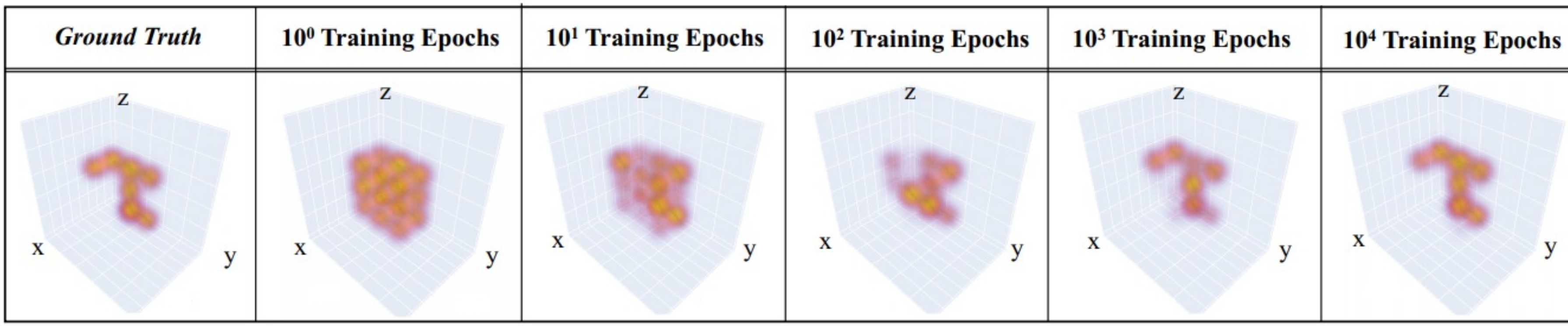
- Formulate RIS configuration selection as a Markov decision process (MDP) where RIS selects each element in $\boldsymbol{C}$ sequentially as follows
  - **State**: Currently selected phase shifts in $\boldsymbol{C}$.
  - **Action**: RIS select the phase shift of the next element following $\boldsymbol{\pi}$.
  - **Transition**: A new element in $\boldsymbol{C}$ is determined, until all of $\boldsymbol{C}$ is selected.
  - **Reward**: After all the elements in $\boldsymbol{C}$ is selected, a data set of random $\boldsymbol{p}$ is generated, and the corresponding Rx signal $\tilde{\boldsymbol{y}}$ are obtained.
    The negative CE loss between $\boldsymbol{p}$ and $\boldsymbol{f}^{w}(\tilde{\boldsymbol{y}})$ is adopted as the reward.
- A replay buffer $\mathcal{B}$ stores experiences of *state, action, and reward* tuples.
- Policy $\boldsymbol{\pi}$ is modeled by a neural network and updated to improves the reward of RIS using the sampled experiences in $\mathcal{B}$.

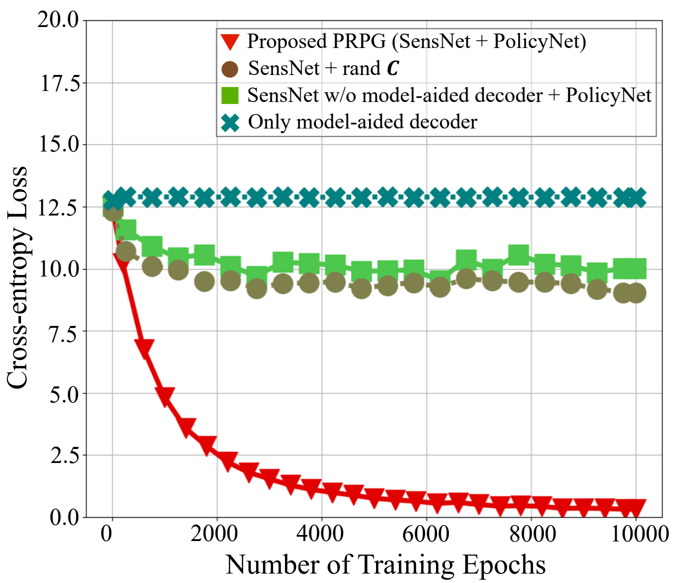
Updating mapping function $\boldsymbol{f}^{w}$

- Given the experiences in $\mathcal{B}$, $\boldsymbol{f}^{w}$ is updated to reduce the CE loss between the mapping result $\hat{\boldsymbol{p}}$ and label $\boldsymbol{p}$ in the data set by using supervised learning.
- The rewards recorded in $\mathcal{B}$ are re-calculated given the updated $\boldsymbol{f}^{w}$.

Iterate until converge

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 III: RIS aided Ubiquitous 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

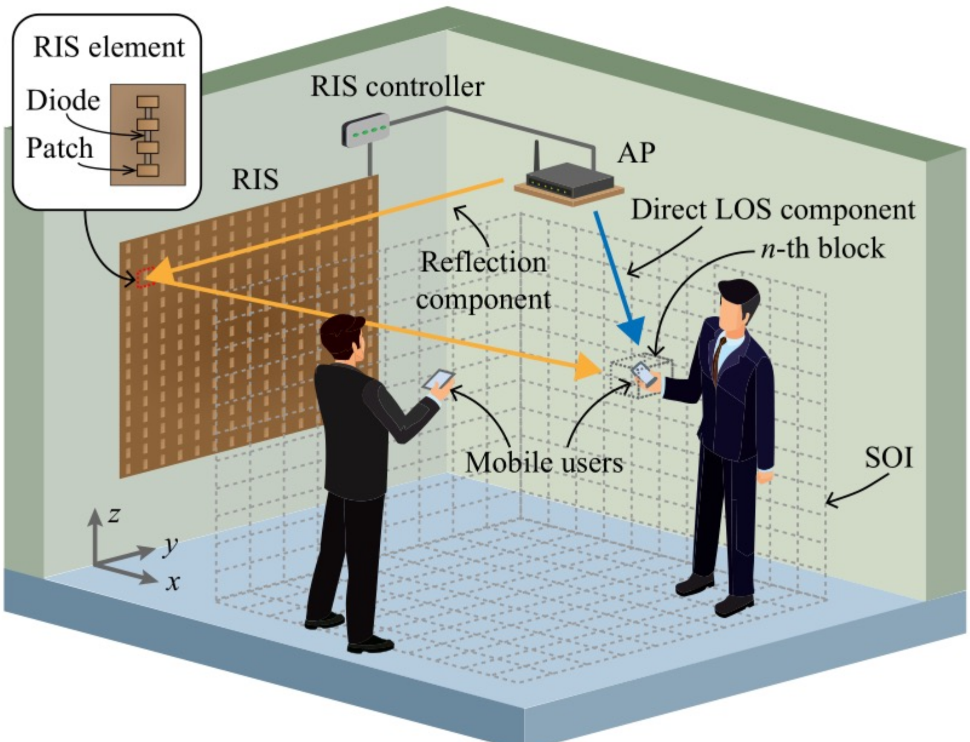
- AP: sends signals to the RIS and mobile users.
- RIS: reflects the signals from the AP to the users.
- Users: measure the RSS for positioning.
- Space of Interest (SOI): is discretized into *N* blocks to represent users' positions.

RIS Model

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

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

- Configuration $\boldsymbol{c}$: the vector of all the elements' states



System Model

RSS Model

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

$$s_n(\boldsymbol{c}) = s^t + 20\log_{10}\left|h_{\mathrm{lo}} + \sum_{m\in\mathcal{M}} h_{m,n}(c_m)\right| + \xi.$$

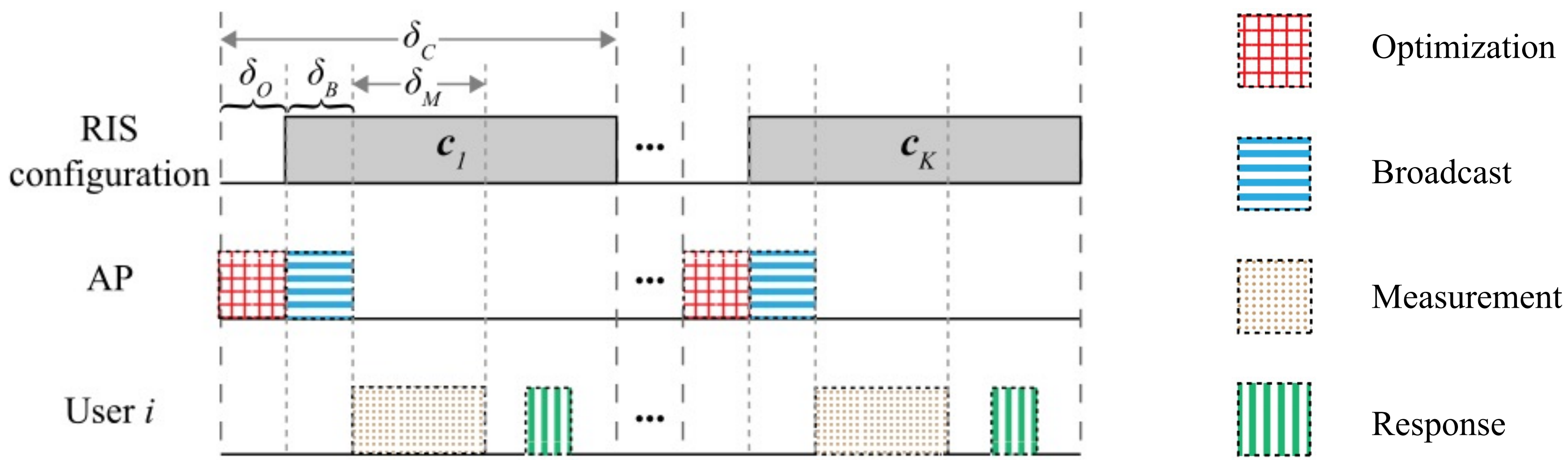
Transmission power of AP

Log-normal shadowing component

Positioning Protocol

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

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



Problem Formulation

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

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

- $p_{i,n}^k$: 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.
- $\mathbb{P}(s_i^k | \boldsymbol{c}^k, n)$: probability that user i receives s_i^k under $\boldsymbol{c}^k$ 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:

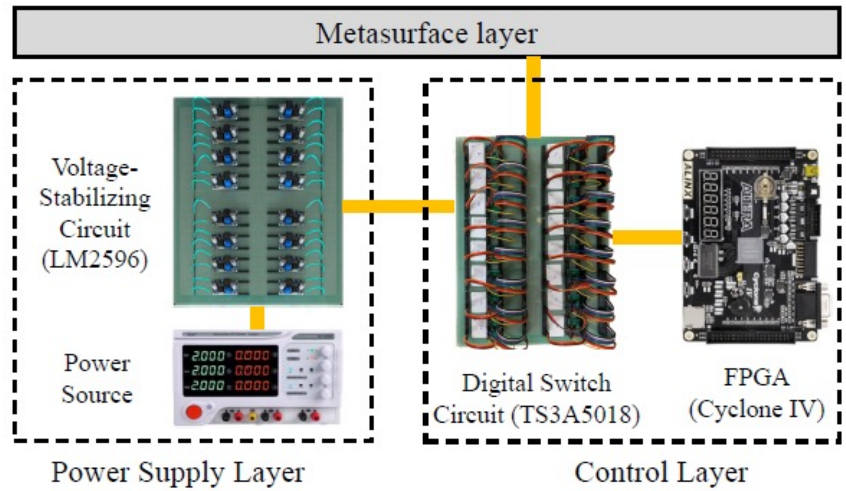
- Metasurface layer
  - Size: 69 × 69 × 0.52 cm^3
  - 4 phase shifts (interval $\frac{\pi}{2}$)
- Control layer
- Power Supply Layer

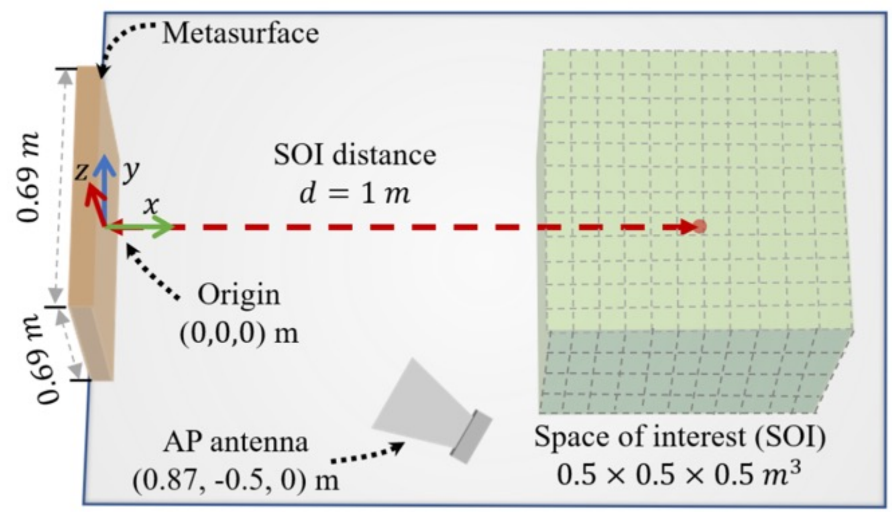
AP and user modules:

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

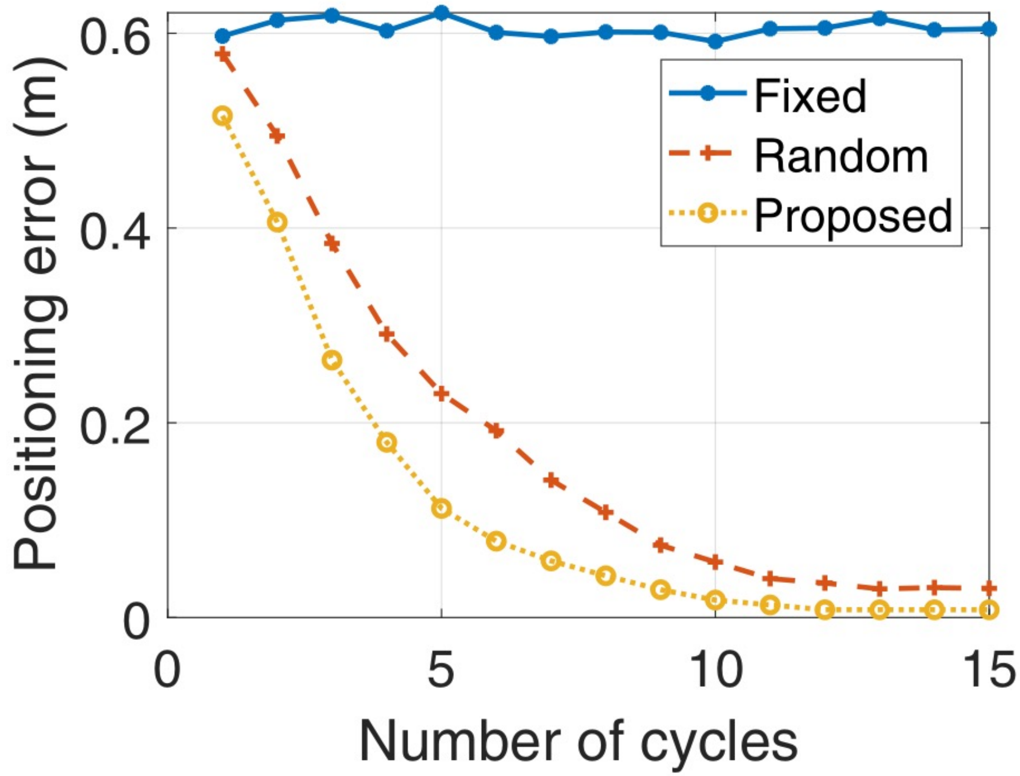
Space of interest (SOI)

- Size: 0.5 × 0.5 × 0.5 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.

Potential Future Directions

High-resolution sensing

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

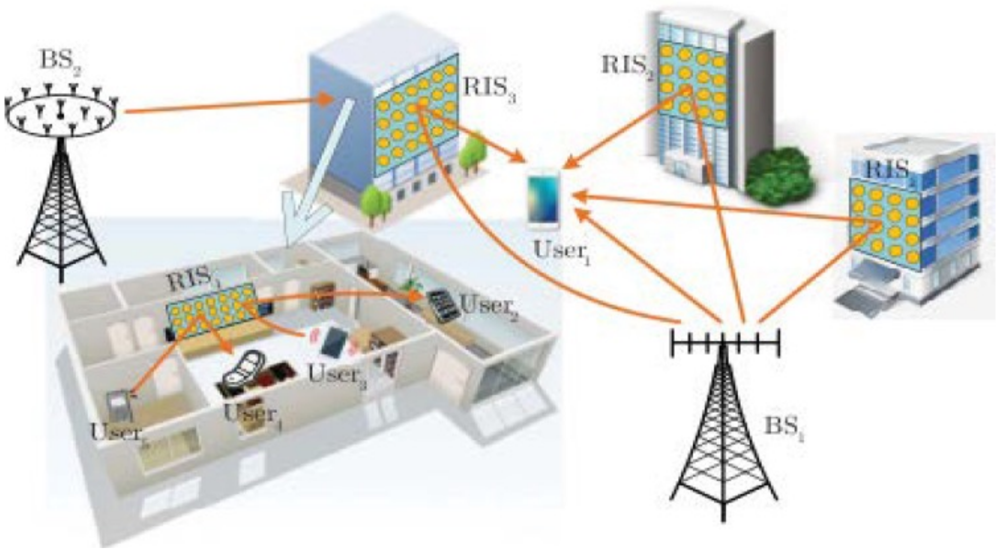
Simultaneous localization and mapping (SLAM)

- Time-varying states and objects, which is unknown
- Movements of objects on slow time scales
- High definition map

Other issues

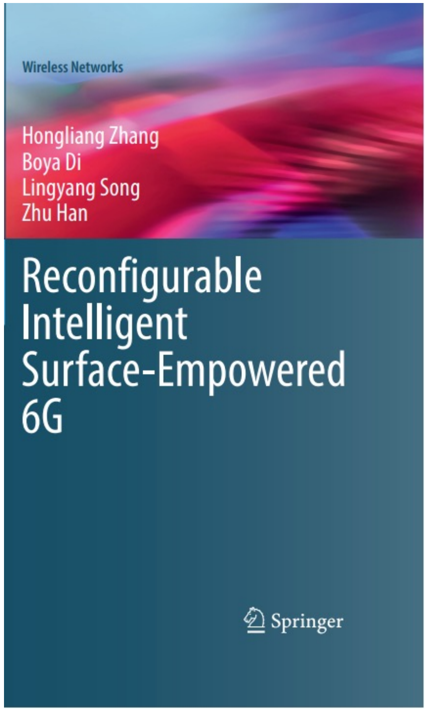
- Context-awareness
- Security and privacy

For communication, please check our other tutorial slides



Conclusions

- RIS is a promising paradigm for future wireless sensing applications
  - Control and customize favorable radio environments
  - Provide high accuracy contact/contactless sensing with wireless data gathering
  - If mirrors can be controlled, Bruce Lee can do a better localization job.
- We explore different aspects related to RIS-aided sensing and localization
  - Posture recognition
  - RF 3D shape sensing
  - Ubiquitous positioning



Publications

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., to be published.

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.

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