



深圳大学
SHENZHEN UNIVERSITY

Transformer-Based Channel Feedback for RIS-Aided Wireless Communication Systems

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1. Research Background

2. Research Content

2.1 Quan-Transformer Based Channel Feedback for RIS-Aided Wireless Communication Systems

2.2 Distributed Learning-Based Channel Estimation and Feedback for RIS-Aided Wireless Communications

3. Summary

■ 6G—A National Infrastructure (Mobile Communication Industry)

➤ 1G → 5G (1980s-2020)

The essence of modern mobile communication:
enhancing **electromagnetic wave coverage intensity**

- Increasing antenna density——Massive MIMO
- More densely deployed base stations——Ultra-Dense Networks
- Higher frequency bands——Sub-6G/Millimeter-wave/and Terahertz
- **Power Consumption Bottleneck:** 5G consumes three times more power than 4G while covering only one-third of the area.

In 2019, the combined profit of the three major telecom operators was 138.4 billion CNY

In 2018, electricity costs: 24 billion (4G)→ 216 billion (5G)

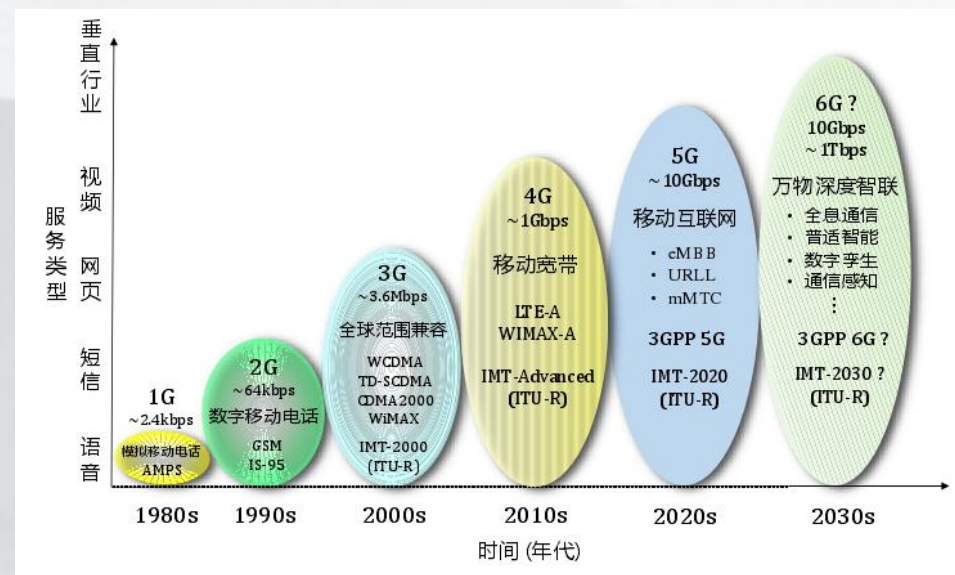


Figure 1: Evolution process of mobile communications

➤ 6G (2020-2030)

- Further improvement in key performance indicators
- Green communication (**carbon peak, carbon neutrality**)
- 5G (Internet of Everything) → 6G (Intelligence of Everything)
- Intrinsic energy efficiency and intrinsic intelligence

Facing tight spectrum resources, sharply increasing energy consumption, and complex propagation environments, traditional "stacked" technological approaches are insufficient to meet the future demands of 6G systems for green, efficient, and adaptive communication. There's an urgent need to shift from traditional "passively adaptive" channels to "programmable environmental control", leading to the advent of Intelligent Reconfigurable Surfaces (RIS) [1].

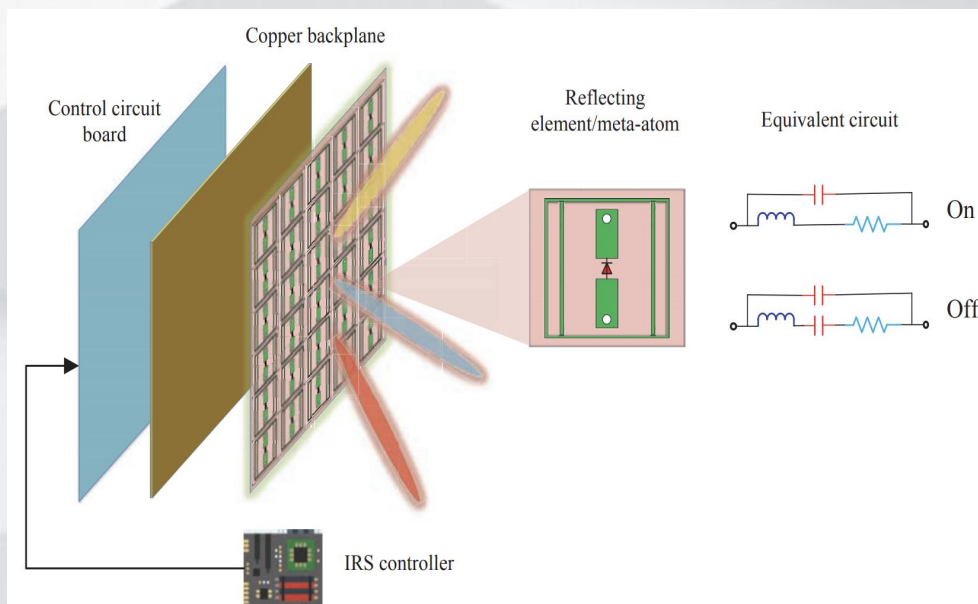


Figure 3: Structural principle of RIS

Low Hardware Cost: Utilizing information metamaterials [1] (PIN diodes, varactors)

Low Operational Cost: Low power consumption, nearly passive (control circuits)

Low Deployment Cost: Lightweight and thin two-dimensional surfaces

Advantages of RIS

- RIS enhances communication system performance through the deployment of a large number of reflective units.
- However, these advantages depend critically on the accurate acquisition of downlink channel state information (CSI) by the base station.

Why do we need channel feedback?

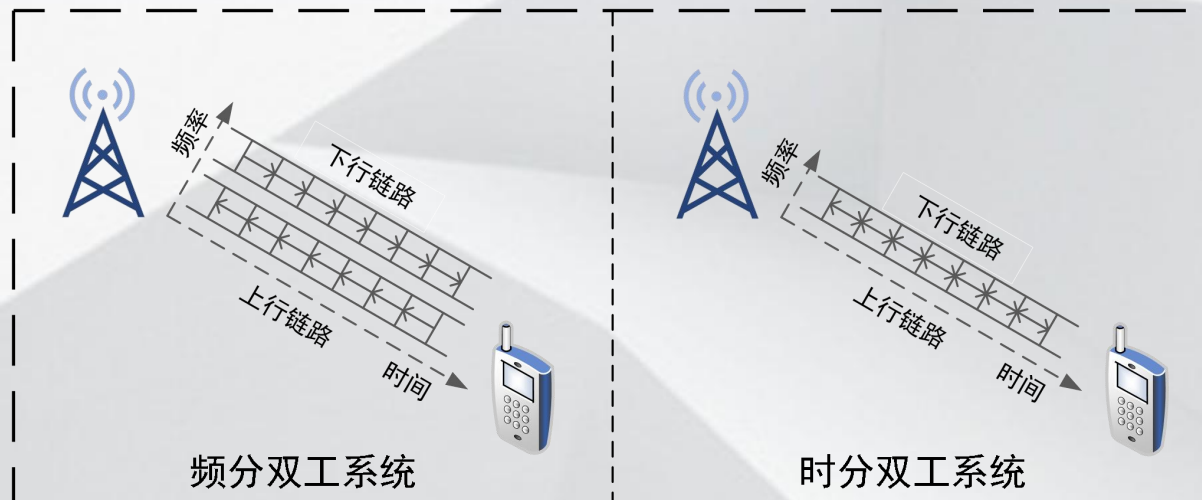


Figure 1: Operational principles of FDD and TDD systems

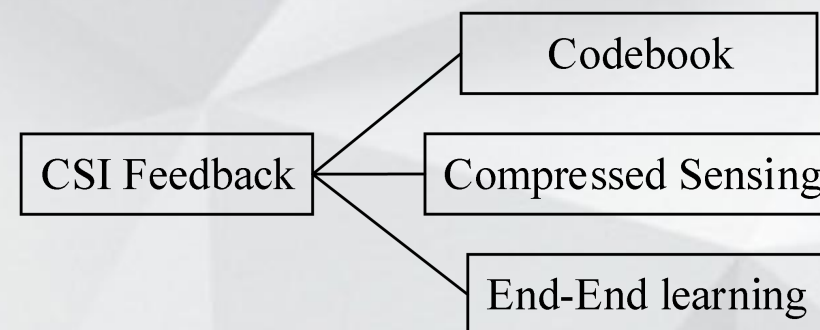
Necessity of CSI Feedback in FDD Systems

- ◆ Due to weak channel reciprocity in FDD systems, downlink CSI is estimated at the user side and transmitted back to the base station via feedback channels.

Numerous antennas and reflecting units ensure system performance^[2]



High-dimensional CSI estimation and feedback are major challenges in RIS-assisted systems



[2] H. Guo, Y. -C. Liang, J. Chen and E. G. Larsson, "Weighted Sum-Rate Maximization for Reconfigurable Intelligent Surface Aided Wireless Networks," IEEE Transactions on Wireless Communications, vol. 19, no. 5, pp.

Consider a RIS-aided wireless communication system, the downlink signal received at the UE can be represented as:

$$\begin{aligned} y &= (\mathbf{g} + \mathbf{h}^T \mathbf{\Theta} \mathbf{H}) s + z \\ &= (\mathbf{g} + \mathbf{h}^T \text{diag}(\mathbf{h}^T) \mathbf{H}) s + z, \end{aligned}$$

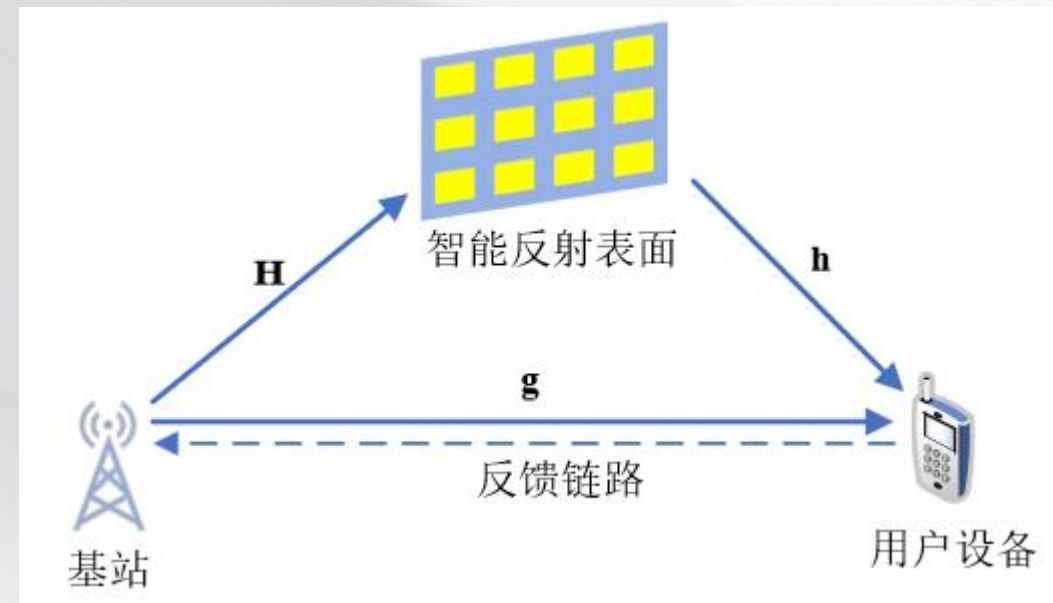
$\mathbf{\Theta} \in \mathbb{C}^{N \times N}$ represents the adjustable phase shift diagonal matrix of RIS as

$$\mathbf{\Theta} = \text{diag}(\mathbf{\theta}^T) = \text{diag}(\omega e^{j\theta_1}, \dots, \omega e^{j\theta_n}, \dots, \omega e^{j\theta_N}),$$

In this work, the objective of channel feedback is the cascaded (BS-RIS-UE) CSI. The cascaded CSI at UE can be expressed as

$$\mathbf{H}_{\text{DL}} = \text{diag}(\mathbf{h}^T) \mathbf{H}.$$

Considering the widely used ray-based channel model [4], both the BS-RIS and RIS-UE channels are modeled accordingly.



RIS-aided wireless communication system

[3] W. Xie, **J. Zou**, J. Xiao, M. Li and X. Peng, "Quan-Transformer Based Channel Feedback for RIS-Aided Wireless Communication Systems," IEEE Communications Letters, vol. 26, no. 11, pp. 2631-2635, Nov. 2022.

[4] P. Wang, J. Fang, H. Duan and H. Li, "Compressed Channel Estimation for Intelligent Reflecting Surface-Assisted Millimeter Wave Systems," IEEE Signal Processing Letters, vol. 27, pp. 905-909, 2020.

The BS-RIS channel in the spatial domain can be expressed as

$$\mathbf{H} = \sum_{i=1}^{L_1} \rho_i \mathbf{m}(p_{1,i}, q_{1,i}) \mathbf{n}(p_i^{\text{AOD}}),$$
$$\mathbf{m}(p_{1,i}, q_{1,i}) = \frac{1}{\sqrt{N}} [e^{j2\pi n_1 p_{1,i}}]^T \otimes [e^{j2\pi n_2 q_{1,i}}]^T,$$
$$\mathbf{n}(p_i^{\text{AOD}}) = \frac{1}{\sqrt{M}} [e^{j2\pi m p_i^{\text{AOD}}}]^T,$$

The RIS-UE channel in the spatial domain can be expressed as

$$\mathbf{h} = \sum_{i=1}^{L_2} \xi_i m^H(p_{2,i}, q_{2,i}),$$
$$\mathbf{m}^H(p_{2,i}, q_{2,i}) = \frac{1}{\sqrt{N}} [e^{j2\pi n_1 p_{2,i}}]^T \otimes [e^{j2\pi n_2 q_{2,i}}]^T,$$

The cascaded channel in the spatial domain is transformed into a sparse channel by applying 2D-DFT

$$\mathbf{H}_{\text{IN}} = \mathbf{F}_d \mathbf{H}_{\text{DL}} \mathbf{F}_a^H,$$

Assuming perfect channel estimation without errors, the UE first compresses the CSI using an encoder, then converts it into a bitstream through uniform quantization. The quantized CSI can be represented as

$$\mathbf{H}_{\text{bit}} = Q(f_{\text{encode}}(\mathbf{H}_{\text{IN}}, \theta_1)),$$

When the BS receives the compressed CSI, it first passes through a dequantizer and then a decoder to recover the original CSI. The recovered CSI is represented as

$$\hat{\mathbf{H}} = f_{\text{decode}}(P(\mathbf{H}_{\text{bit}}, \theta_2)),$$

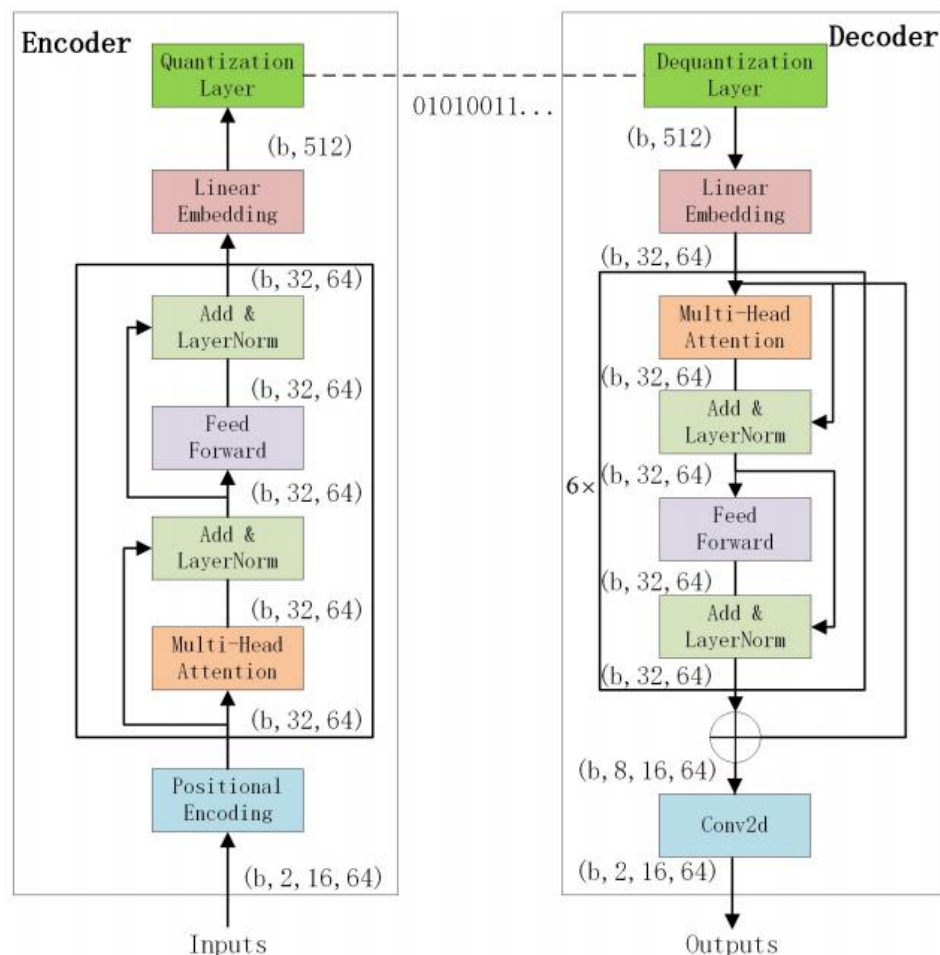
The encoder-decoder network uses the Mean Squared Error (MSE) as the loss function to optimize the network model parameters.

$$(\hat{\theta}_1, \hat{\theta}_2) = \arg \min_{\theta_1, \theta_2} \|\mathbf{H}_{\text{IN}} - \hat{\mathbf{H}}\|_2^2.$$

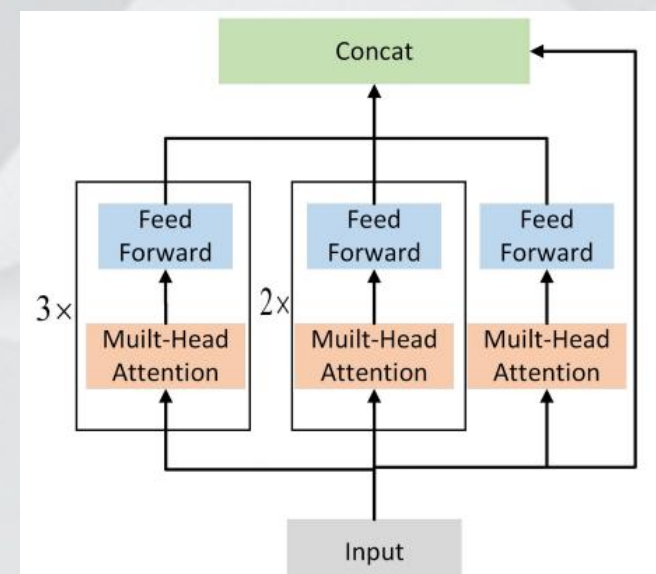
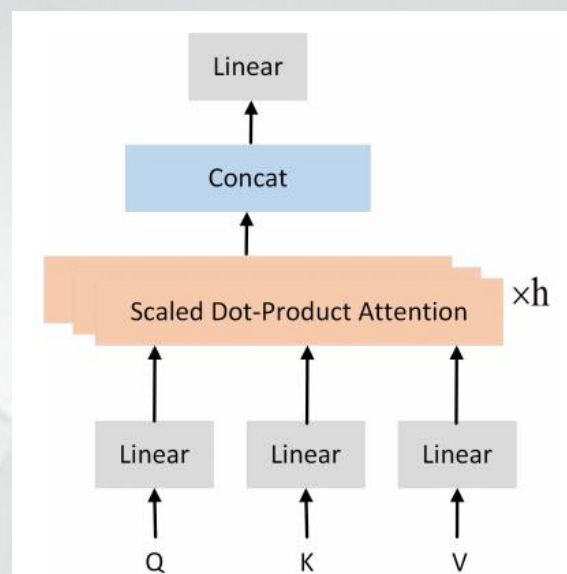
NMSE and CR are used to evaluate the network performance.

$$\text{NMSE} = \mathbb{E} \left\{ \frac{\|\mathbf{H}_{\text{IN}} - \hat{\mathbf{H}}\|_2^2}{\|\mathbf{H}_{\text{IN}}\|_2^2} \right\}, \quad \text{CR} = \frac{2NM}{L},$$

Proposed method



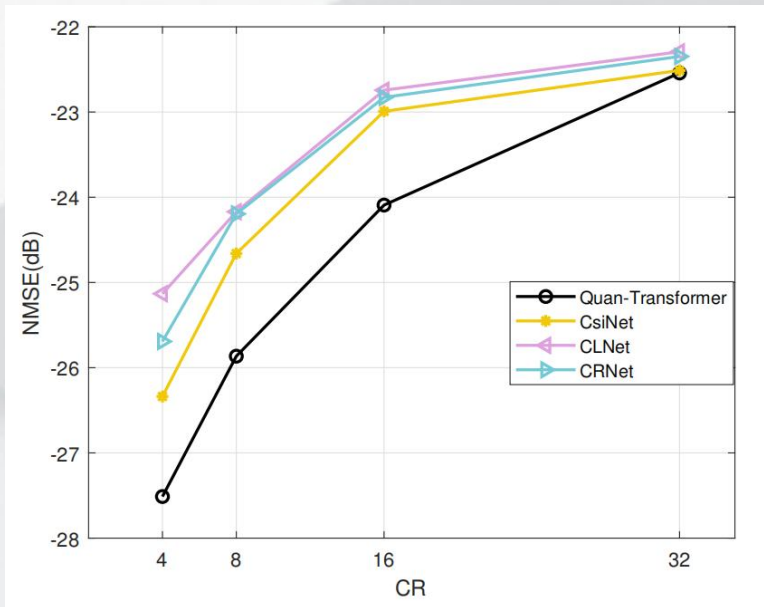
Inspired by the **autoencoder** architecture, the encoder and decoder are deployed at the user side and the base station side, respectively, to perform **CSI compression and reconstruction**. The backbone network employs a Transformer mainly because, compared to traditional CNNs, the Transformer has **stronger global modeling capabilities** and more flexible attention mechanisms, enabling it to more effectively capture **long-range dependencies** and **complex features** in the CSI, thereby improving the accuracy and robustness of channel feedback.



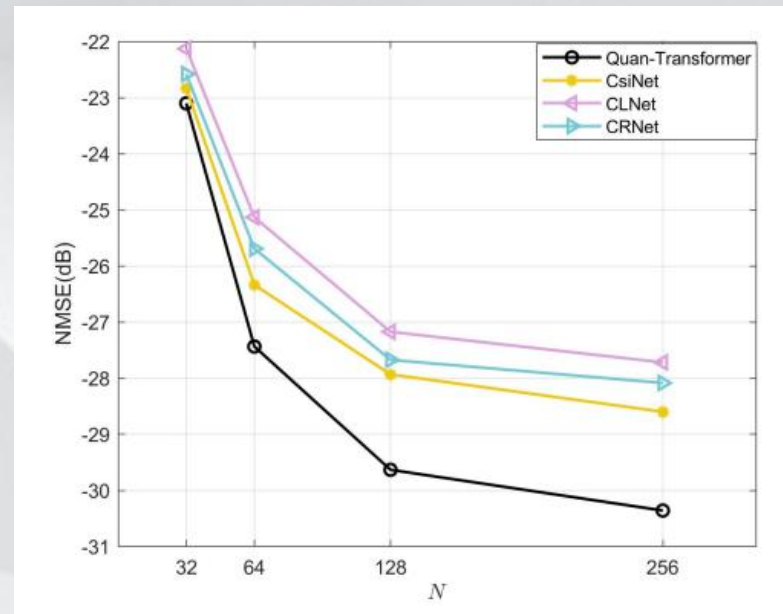
Numerical Results



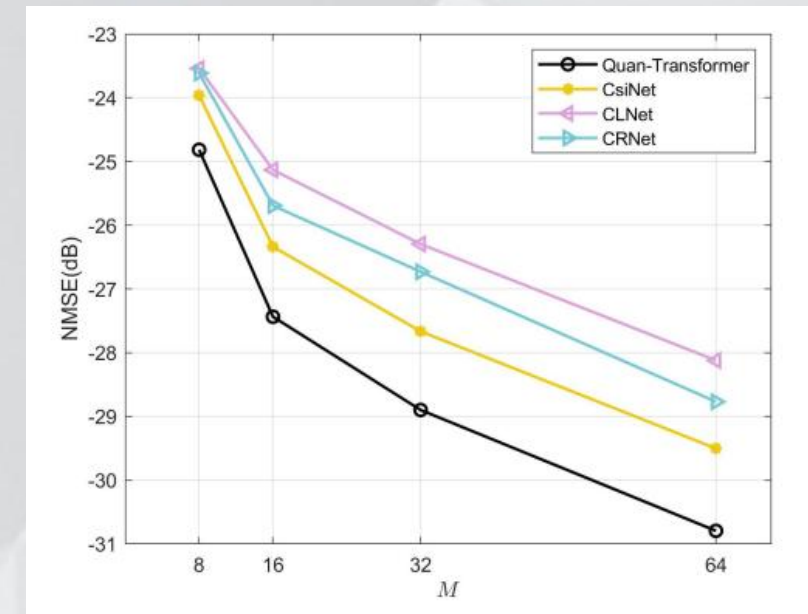
The experiment compares the NMSE performance of the **proposed channel feedback scheme** with **other schemes** under different **compression ratios**. Additionally, the impact of varying the **number of reflecting elements** and **antennas** on the NMSE performance of channel feedback is also demonstrated.



NMSE performance of different channel feedback schemes under various compression ratios

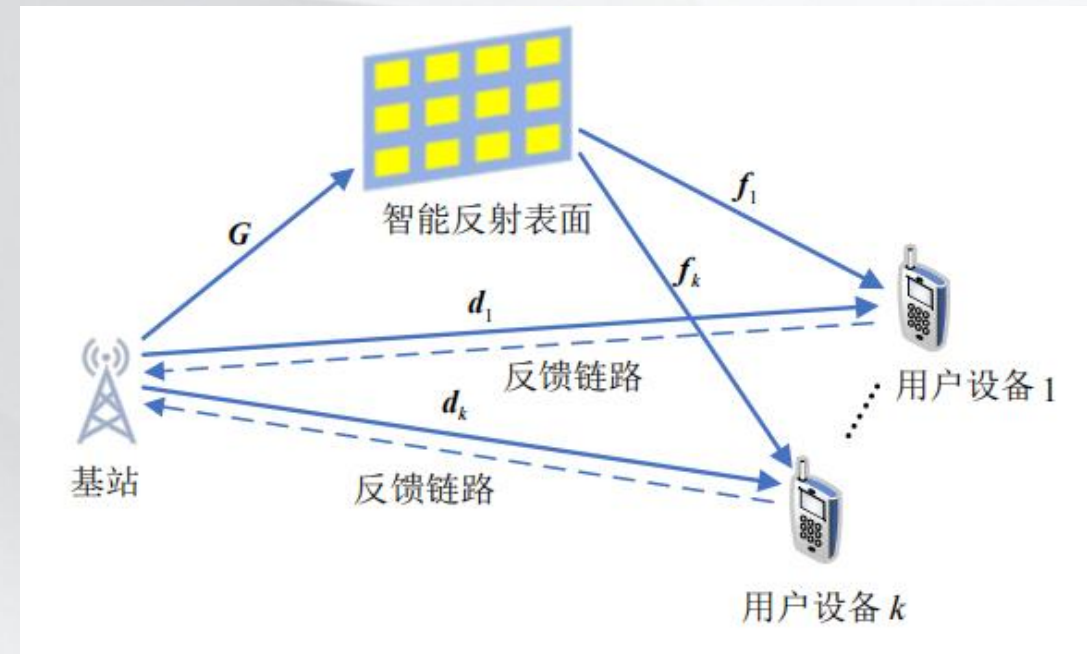


NMSE performance of different channel feedback schemes under varying numbers of reflecting elements



NMSE performance of different channel feedback schemes under varying numbers of antennas

- Most existing RIS feedback schemes assume **ideal CSI**, overlooking the impact of **channel estimation errors**. A key challenge lies in designing robust feedback mechanisms that remain effective under practical estimation uncertainty.
- In scenarios with limited device resources and restricted access to raw CSI, it is essential to develop **distributed feedback** methods that **preserve user privacy** while minimizing communication overhead.
- The **conventional decoupled design** of channel estimation and feedback leads to redundant computations and suboptimal performance. Integrating both processes can **reduce system complexity** and enhance end-to-end robustness and efficiency.



RIS-aided multi-user wireless communication system

Consider an RIS-aided multi-user system under the FDD mode, the BS sends known pilot symbols to U_k over T time slots for downlink channel estimation. The received signal $y_{k,t}$ at U_k in the t -th time slot is given by

$$y_{k,t} = (\mathbf{d}_k + \mathbf{f}_k^T \text{diag}(\boldsymbol{\theta}_t^T) \mathbf{G}) \mathbf{w}_k s_{k,t} + z_{k,t} \\ = \phi_t \mathbf{H}_k \mathbf{w}_k s_{k,t} + z_{k,t},$$

where $\phi_t = (1, \boldsymbol{\theta}_t^T) \in \mathbb{C}^{1 \times (N+1)}$, $\mathbf{H}_k = [\mathbf{d}_k; \text{diag}(\mathbf{f}_k^T) \mathbf{G}] \in \mathbb{C}^{(N+1) \times M}$, $z_{k,t}$ represents additive white Gaussian noise (AWGN).

In traditional least squares methods, the time slot T for channel estimation must satisfy $T \geq (N+1) \times M$ [6].

Assuming $s_{k,t} = 1$, the overall measurement matrix $\mathbf{y}_k = [\mathbf{y}_{k,1}, \mathbf{y}_{k,2}, \dots, \mathbf{y}_{k,T}]^T \in \mathbb{C}^{T \times 1}$ is given by

$$\mathbf{y}_k = \boldsymbol{\Theta} \mathbf{H}_k \mathbf{w}_k + \mathbf{z}_k,$$

According to $\text{vec}(\mathbf{ABC}) = (\mathbf{C}^T \otimes \mathbf{A}) \text{vec}(\mathbf{B})$,

$$\mathbf{y}_k = \boldsymbol{\Psi} \text{vec}(\mathbf{H}_k) + \mathbf{z}_k,$$

where $\boldsymbol{\Psi} = (\mathbf{w}_k^T \otimes \boldsymbol{\Theta}) \in \mathbb{C}^{T \times (N+1)M}$, $\text{vec}(\mathbf{H}_k) \in \mathbb{C}^{(N+1)M \times 1}$.

All channels use the Rician fading model. Taking the BS-RIS channel as an example,

$$G = \left(\sqrt{\frac{\beta_{\text{BI}}}{\beta_{\text{BI}} + 1}} G_{\text{LOS}} + \sqrt{\frac{1}{\beta_{\text{BI}} + 1}} G_{\text{NLOS}} \right) \sqrt{\alpha^{\text{BI}}}$$

Then the goal of channel estimation and feedback is

$$\mathbf{H}_k = [\mathbf{d}_k; \text{diag}(\mathbf{f}_k^T) \mathbf{G}]$$

[5] J. Zou, Q. Mao, J. Xiao, S. Liu and Y. Liang, "Distributed Learning-Based Channel Estimation and Feedback for RIS-Aided Wireless Communications," IEEE Wireless Communications Letters, vol. 14, no. 2, pp. 460-464, Feb. 2025, doi: 10.1109/LWC.2024.3509612.

[6] L. Dai and X. Wei, "Distributed Machine Learning Based Downlink Channel Estimation for RIS Assisted Wireless Communications," in IEEE Transactions on Communications, vol. 70, no. 7, pp. 4900-4909, July 2022.

The channel estimation is modeled as

$$\mathcal{F}(\mathbf{H}_k^{est}) = f_{est}(\mathcal{F}(\mathbf{Y}_k), \nu),$$

$$L_{est}(\nu) = \frac{1}{N_t} \sum_{j=1}^{N_t} \left\| \mathcal{F}(\mathbf{H}_k^{(j)}) - \mathcal{F}(\mathbf{H}_k^{est(j)}) \right\|_2^2.$$

The channel feedback is modeled as

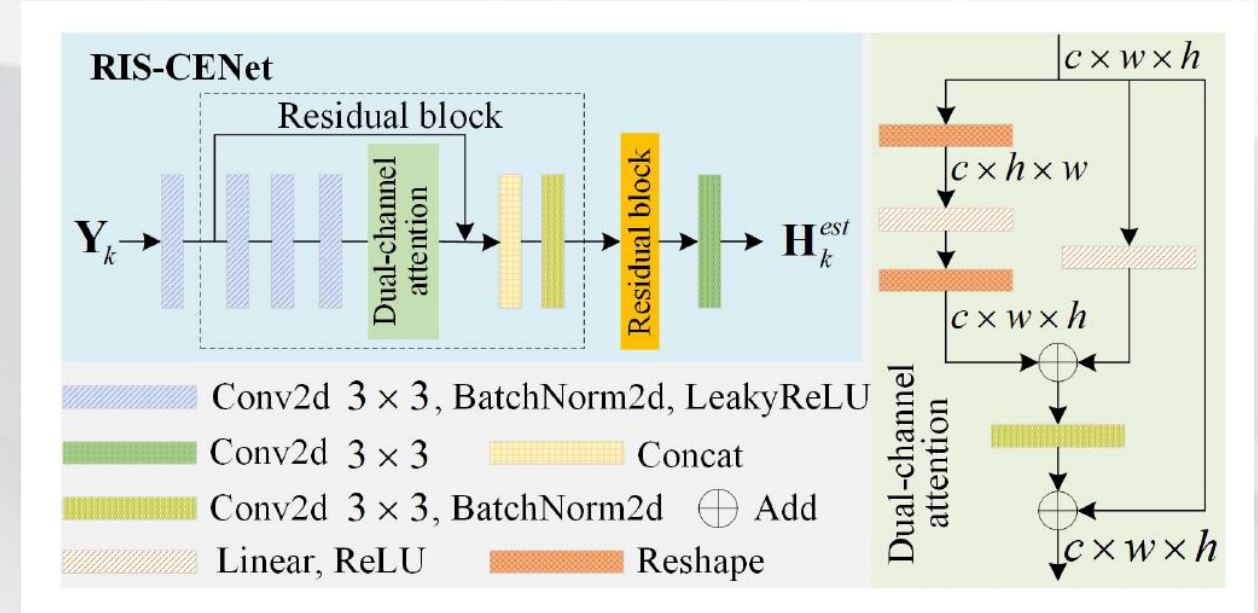
$$\mathbf{H}_k^{bit} = Q(f_e(\mathcal{F}(\mathbf{H}_k^{est}), \varsigma)),$$

$$\mathcal{F}(\mathbf{H}_k^{fd}) = f_d(D(\mathbf{H}_k^{bit}), \rho),$$

$$L_{fd}(\varsigma, \rho) = \frac{1}{N_t} \sum_{j=1}^{N_t} \left\| \mathcal{F}(\mathbf{H}_k^{(j)}) - \mathcal{F}(\mathbf{H}_k^{fd(j)}) \right\|_2^2.$$

The compression ratio is expressed as

$$CR = \frac{2 \times M \times (N + 1)}{L}.$$



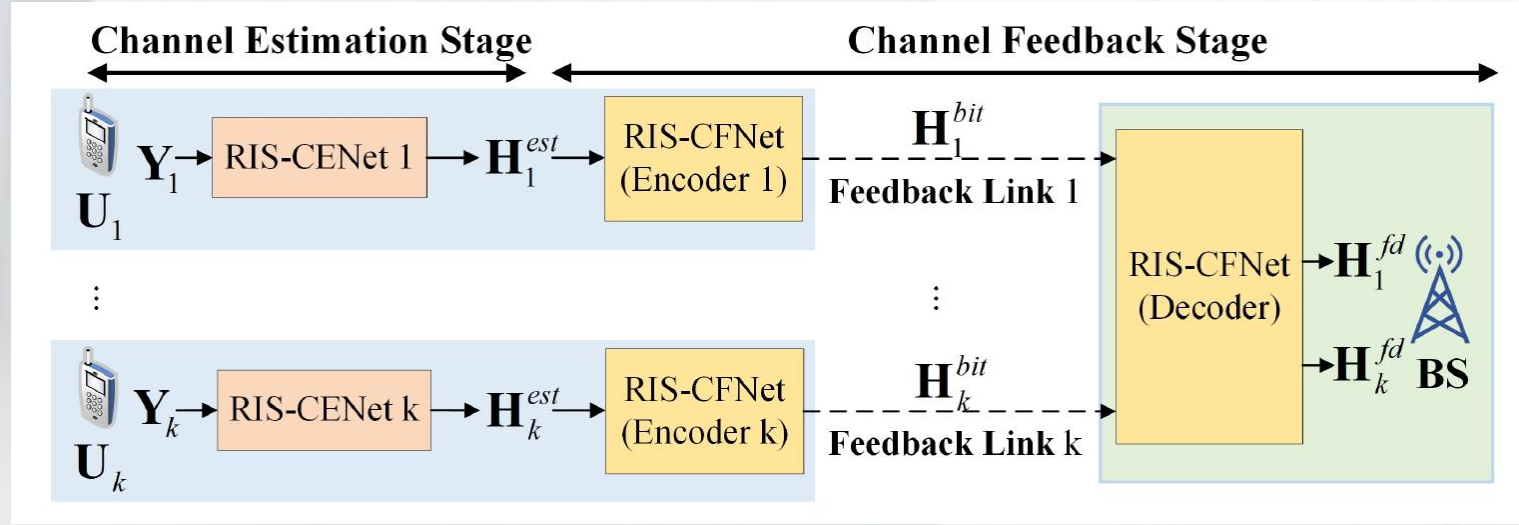
A **multi-channel attention mechanism** is designed to separately extract features along the **reflecting element** and **antenna** dimensions, enabling a more comprehensive modeling of the channel structure and thereby enhancing the accuracy of channel estimation.

Proposed method



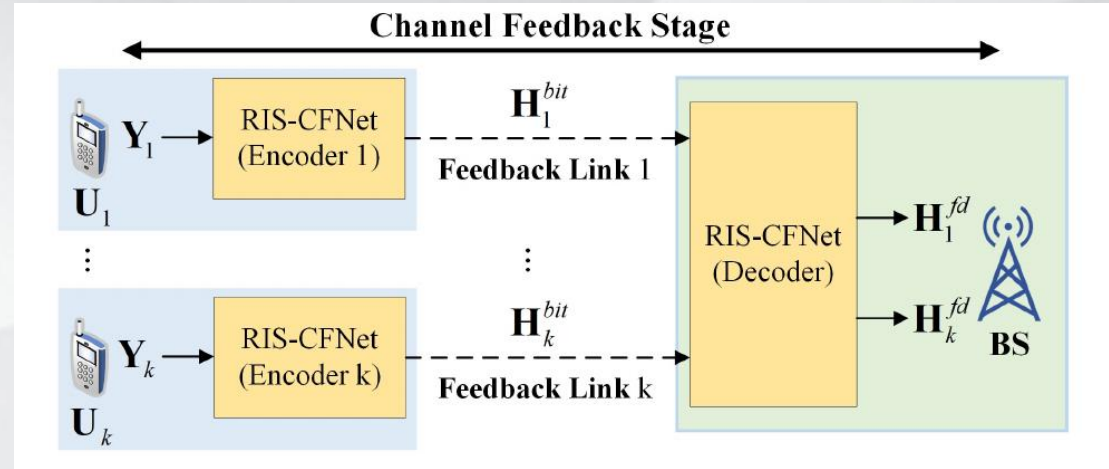
The implementation process of Distributed Scheme I (which adopts the **traditional separate design of channel estimation and feedback**) is as follows:

$$\begin{cases} \mathcal{F}(\mathbf{H}_k^{est}) = f_{est1}(\mathcal{F}(\mathbf{Y}_k), \nu_1), \\ \mathbf{H}_k^{bit} = Q(f_{encoder1}(\mathcal{F}(\mathbf{H}_k^{est}), \varsigma_1)), \\ \mathcal{F}(\mathbf{H}_k^{fd}) = f_{decoder1}(D(\mathbf{H}_k^{bit}), \rho_1). \end{cases}$$



Inspired by the powerful nonlinear capability of neural networks, the implementation process of **Distributed Scheme II (Integrated Design of Channel Estimation and Feedback)** is as follows:

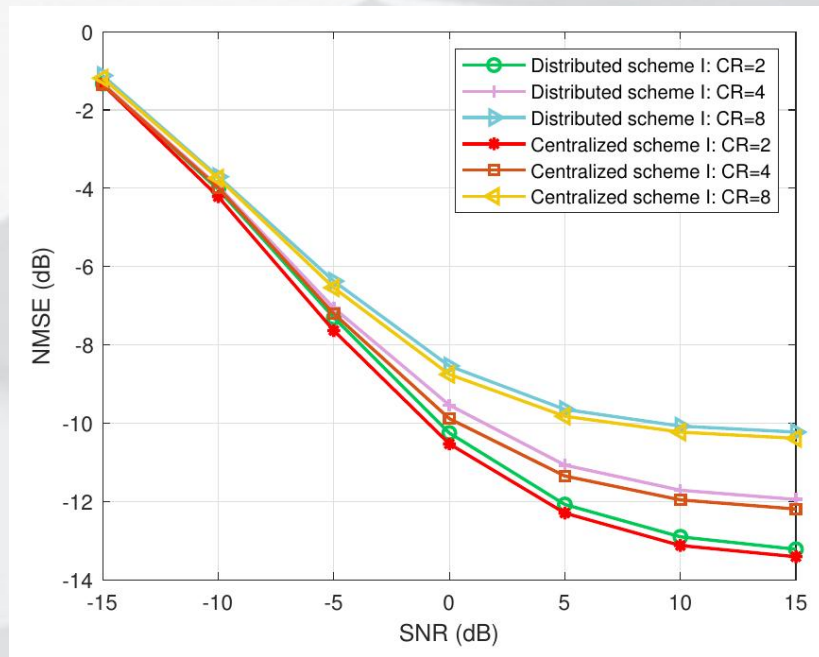
$$\begin{cases} \mathbf{H}_k^{bit} = Q(f_{encoder2}(\mathcal{F}(\mathbf{Y}_k), \varsigma_2)), \\ \mathcal{F}(\mathbf{H}_k^{fd}) = f_{decoder2}(D(\mathbf{H}_k^{bit}), \rho_2). \end{cases}$$



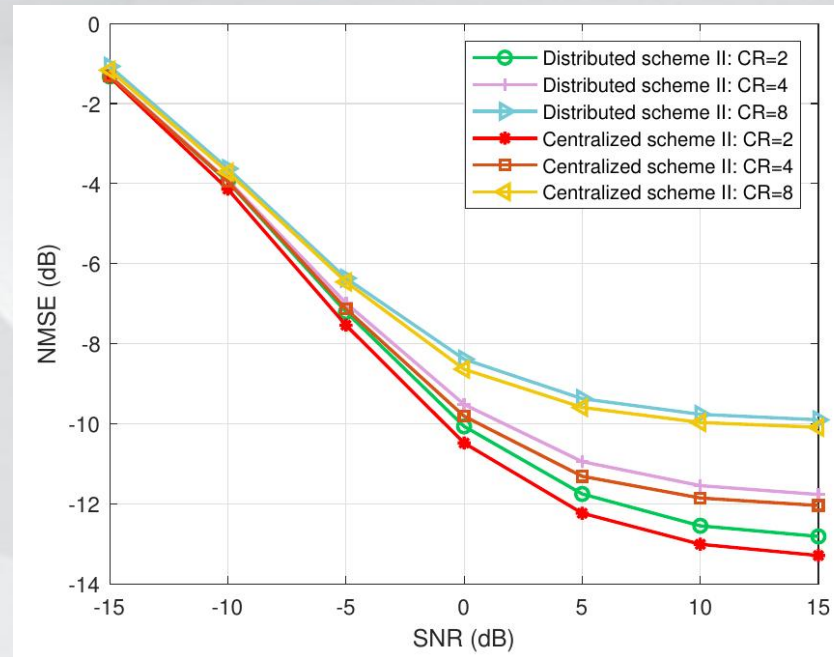
Numerical Results



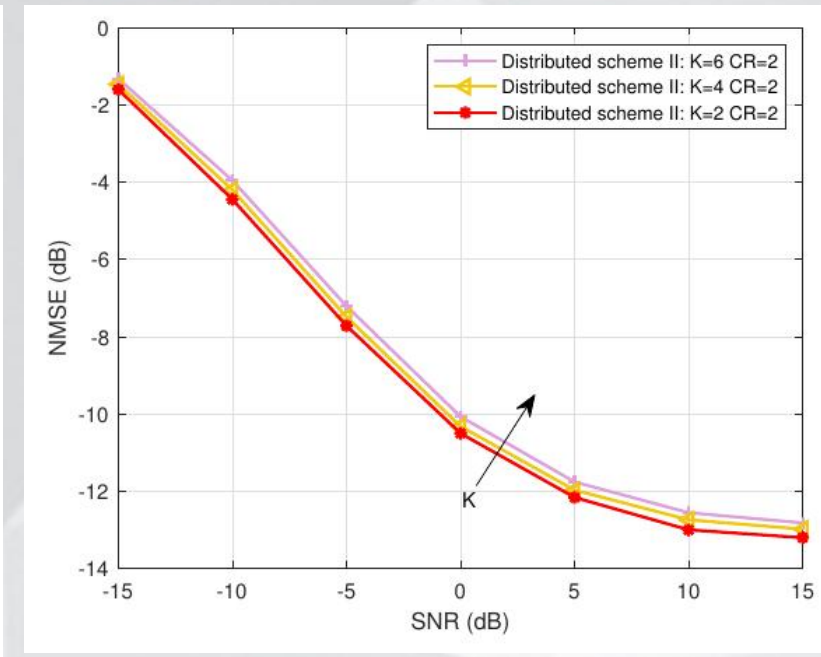
The experiments compare the **NMSE performance** of the **two distributed schemes** with that of the **centralized scheme**. Furthermore, simulations are conducted to evaluate the impact of **different user numbers** on the performance of the distributed schemes.



Centralized vs. Distributed Scheme I



Centralized vs. Distributed Scheme II



NMSE performance with different UEs

Deep learning exhibits remarkable modeling capacity and system adaptability in channel estimation and feedback for RIS-aided wireless communication systems, thereby providing a novel and promising direction for the design of efficient and low-cost feedback mechanisms.

1. Deep Learning-Based Channel Estimation and Feedback for **Multi-Scenario** RIS Systems

(Including near-field/far-field RIS scenarios, multi-hop RIS systems, RIS-Aided UAV communications, etc.)

2. Channel Estimation and Feedback for RIS Systems **Driven by Measurement Data**

Most existing RIS-related studies rely on **idealized simulated channels**. However, in real deployments, they face **channel uncertainty and modeling deviation**. The lack of validation using measured data raises concerns about the generalization capability of these algorithms, thereby limiting their practical applicability.

3. Channel Estimation and Feedback for RIS-Aided Wireless Communication Systems under **Few-Shot and Low-Label Conditions**

How to quickly adapt to varying environments under few-sample and weakly-labeled data constraints has become a pressing and challenging research topic?



Thank you for watching!

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