Precoding-oriented Massive MIMO CSI Feedback Design

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Outline

Motivation

- Downlink frequency division duplexing (FDD) MIMO: the channel state information (CSI) has to be fed back on the uplink

J. Guo, C.-K. Wen, S. Jin, and G. Y. Li, "Overview of deep learning-based CSI feedback in massive MIMO systems," IEEE TCOM, 2022.

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$\Longrightarrow$ **We focus on task-oriented CSI compression**

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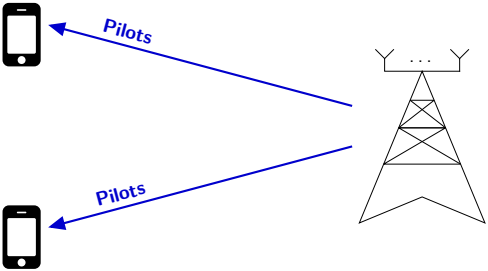
Conventional CSI feedback



Conventional CSI feedback

1) Channel Estimation

2) CSI compression

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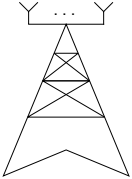

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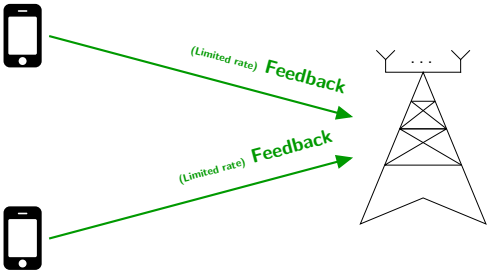

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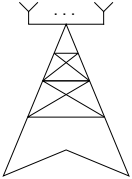
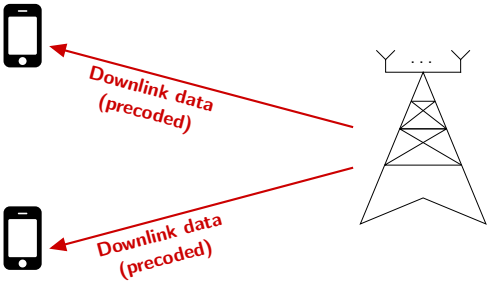


3) CSI reconstruction

4) Determine downlink precoding

Conventional CSI feedback



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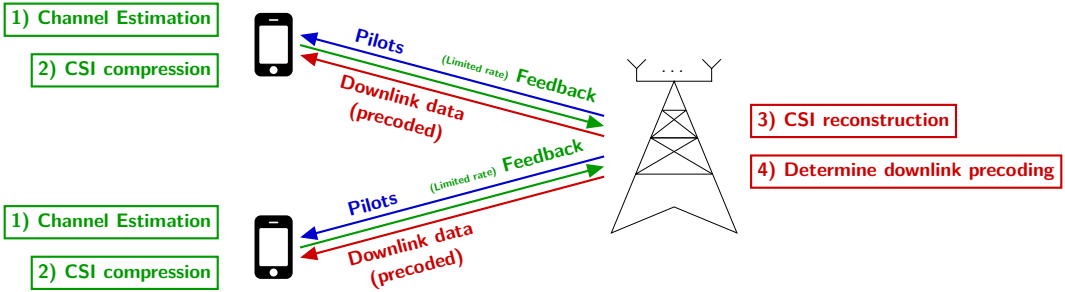

Precoding-oriented CSI feedback

Task: MIMO precoding
Goal: max achievable rate with limited feedback overhead

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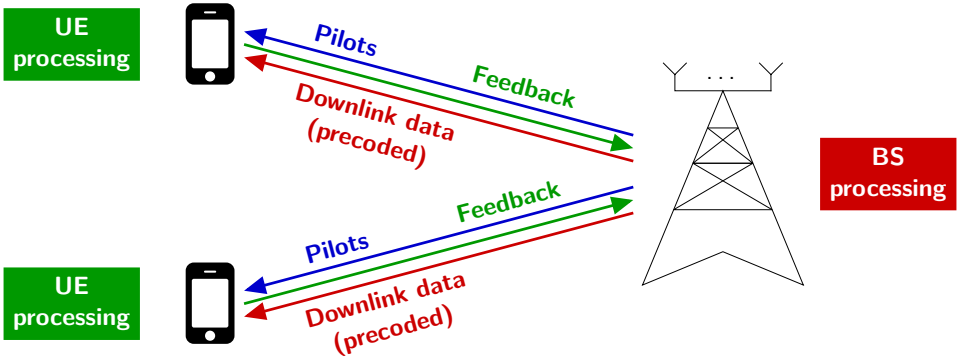


System Model: definitions

- One BS with N_t antennas, K single-antennas users
- Downlink transmitted signal with linear precoding:

$$\mathbf{x} = \sum_{k=1}^{K} \mathbf{v}_k s_k = \mathbf{V}\mathbf{s}$$

- Received signal at k-th user:

$$y_k = \mathbf{h}_k^H \mathbf{v}_k s_k + \sum_{j \neq k} \mathbf{h}_k^H \mathbf{v}_j s_j + z_k$$

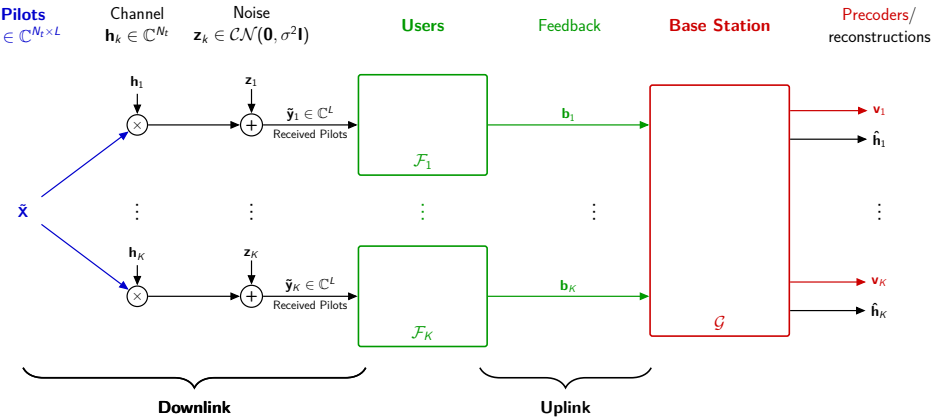
- **Metric**: sum of achievable rates:

$$R = \sum_{k=1}^{K} R_k = \sum_{k=1}^{K} \log_2 \left(1 + \frac{|\mathbf{h}_k^H \mathbf{v}_k|^2}{\sum_{j \neq k} |\mathbf{h}_k^H \mathbf{v}_j|^2 + \sigma^2} \right) \quad (1)$$

System Model: block diagram

We use neural networks to design pilots, feedback scheme $\mathcal{F}$, BS processing $\mathcal{G}$

Goal: max achievable rate with limited feedback overhead



Previous work

Ref	Task-oriented?	Feedback overhead optimization?
[1]	Yes, precoding	No, overhead is fixed with the architecture
[2]	No, channel reconstruction	Yes, Lagrangian loss and entropy coding [3, 4]
Ours	Yes, precoding	Yes, Lagrangian loss and entropy coding [3, 4]

- [3, 4]: image compression with neural networks (autoencoder), the loss function includes a tradeoff between feedback overhead (rate) and image reconstruction performance

[1] F. Sohrabi, K. M. Attiah, and W. Yu, "Deep learning for distributed channel feedback and multiuser precoding in FDD massive MIMO," *IEEE Transactions on Wireless Communications*, vol. 20, no. 7, pp. 4044–4057, 2021.

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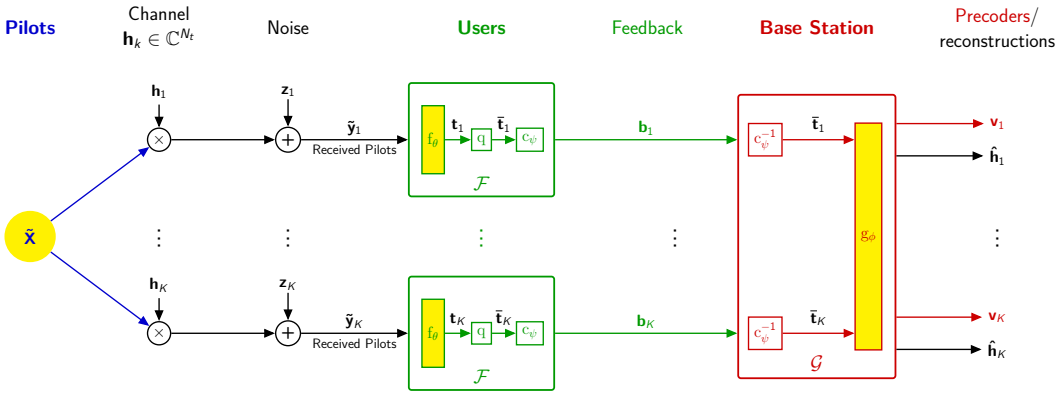
Neural Networks



Neural networks

Pilots $\tilde{\mathbf{X}} \in \mathbb{C}^{N_t \times L}$

- Fully-connected (FC) layer with linear activation and zero bias
- Power constraint: $\|\tilde{\mathbf{x}}_\ell\|_2^2 = P$

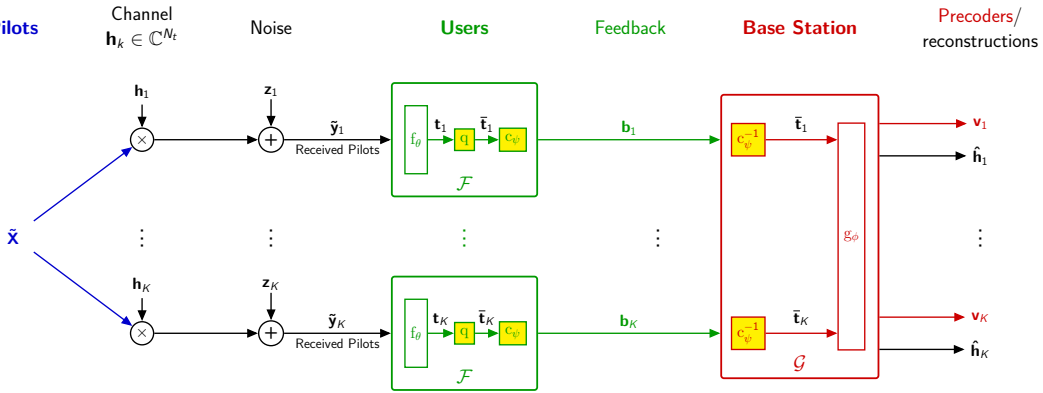
User network f_θ

- DNN with 4 FC layers
- Extracts *semantic features* $\mathbf{t}_k$ from the noisy pilots (per user)

BS network g_ϕ

- DNN with 5 FC layers
- Determines the K precoders from the K semantic features
- Power constraint: $\mathrm{Tr}(\mathbf{V}\mathbf{V}^H) = P$

Feedback Overhead Optimization



Feedback Overhead Optimization

Feedback quantization: DNN output to bitstream — from [Ballé et al., 2017, 2018]

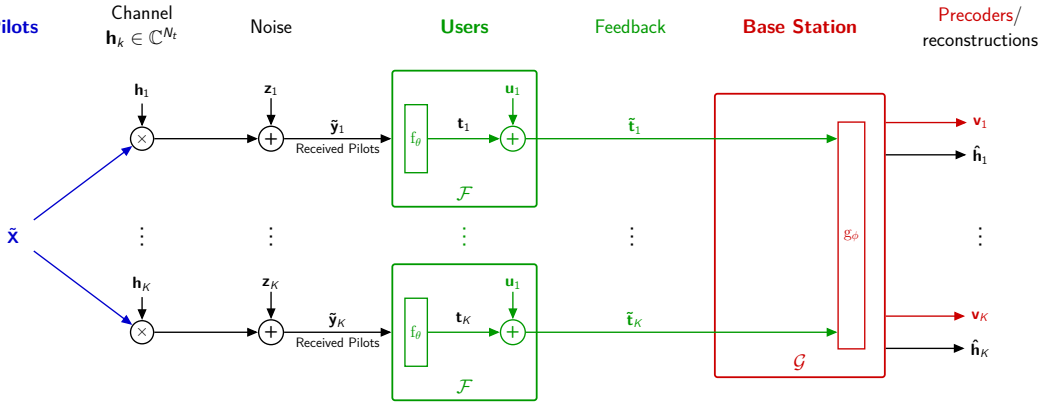
During test time:

- Quantizer q: scalar quantization to closest integer $\Longrightarrow$ quantized features $\bar{\mathbf{t}}_k$
- Entropy coder c_ψ: converts $\bar{\mathbf{t}}_k$ into bit streams $\mathbf{b}_k$
- Entropy decoder c_ψ^{-1}: (lossless) reconstruction $\mathrm{c}_\psi^{-1}(\mathbf{b}_k) = \bar{\mathbf{t}}_k$
- ψ: parameters learned during training $\Longrightarrow \sim$ probability distribution of $\bar{\mathbf{t}}_k$

During training:

- Simulate quantization noise: add $u_k^1, \ldots, u_k^{N_b} \sim \mathcal{U}[-0.5, +0.5]$
- Pseudo-quantized features: $\tilde{\mathbf{t}}_k = \mathbf{t}_k + \mathbf{u}_k$
- Note: the probability distribution of $\tilde{\mathbf{t}}_k$ is a continuous relaxation of the one of $\bar{\mathbf{t}}_k$

Loss Function



$$\mathbf{H} = [\mathbf{h}_1, \ldots, \mathbf{h}_K]$$

$$\mathbf{V} = [\mathbf{v}_1, \ldots, \mathbf{v}_K]$$
$$\hat{\mathbf{H}} = [\hat{\mathbf{h}}_1, \ldots, \hat{\mathbf{h}}_K]$$

Loss Function

Loss function including three possible metrics:

$$\mathcal{L}(\theta, \phi, \psi) = \mathcal{O} - \lambda\mathcal{R} + \gamma\mathcal{D}, \tag{2}$$

- Feedback overhead $\mathcal{O}$: entropy (rate) of the pseudo-quantized features $\tilde{\mathbf{t}}_k$
- Performance $\mathcal{R}$: achievable rates with precoding $\mathbf{V}$
- Distortion $\mathcal{D}$: reconstruction loss when estimating channels $\hat{\mathbf{H}}$
- λ and γ determine the tradeoff between the three components

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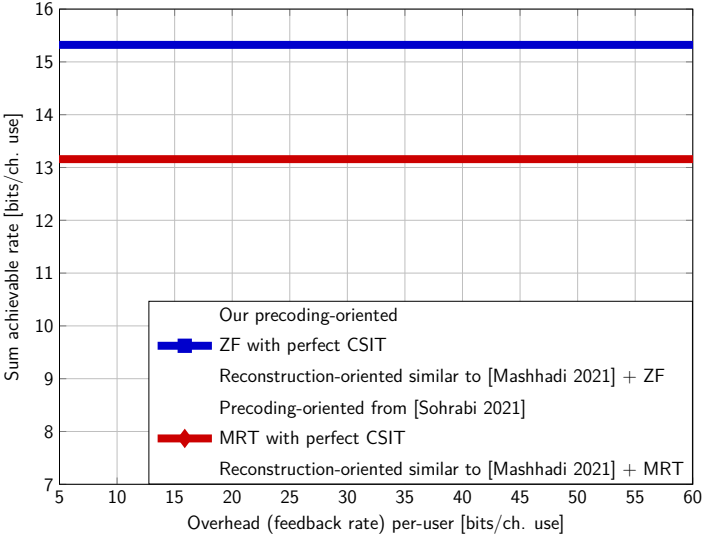
- Feedback overhead $\mathcal{O}$: entropy (rate) of the pseudo-quantized features $\tilde{\mathbf{t}}_k$
  $\mathcal{O}_k(\theta, \psi) = \mathbb{E}_{\mathbf{h}_k, \mathbf{u}_k, \mathbf{z}_k} \left[-\log p_{\tilde{\mathbf{t}}}(\tilde{\mathbf{t}}_k; \psi) \right]$
- Performance $\mathcal{R}$: achievable rates with precoding $\mathbf{V}$
  $\mathcal{R}_k(\theta, \psi, \phi) = \mathbb{E}_{\mathbf{h}_k, \mathbf{U}, \mathbf{Z}} \log_2 \left(1 + \frac{|\mathbf{h}_k^H \mathbf{v}_k|^2}{\sum_{j \neq k} |\mathbf{h}_k^H \mathbf{v}_j|^2 + \sigma^2} \right)$
- Distortion $\mathcal{D}$: reconstruction loss when estimating channels $\hat{\mathbf{H}}$
  $\mathcal{D}(\theta, \psi, \phi) = \mathbb{E}_{\mathbf{H}, \mathbf{U}, \mathbf{Z}} \left\| \mathbf{H} - \hat{\mathbf{H}} \right\|_2^2$
- λ and γ determine the tradeoff between the three components

Results: 2 users, 64 TX antennas, 2-path channel, 8 pilots, SNR = 10dB



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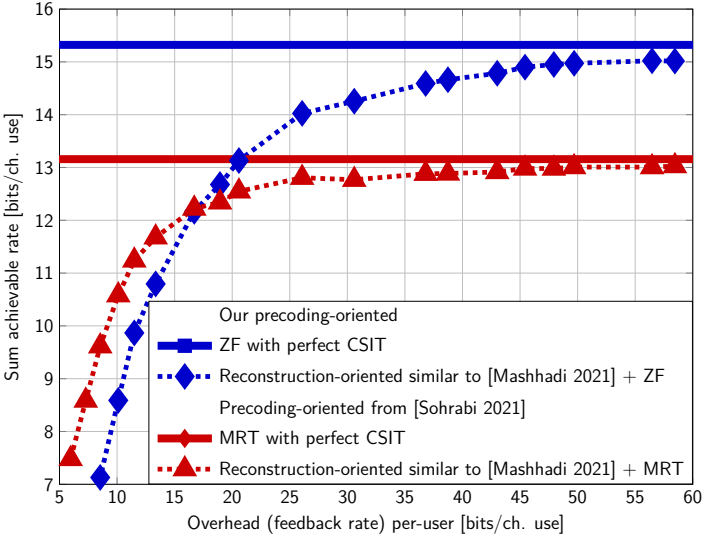

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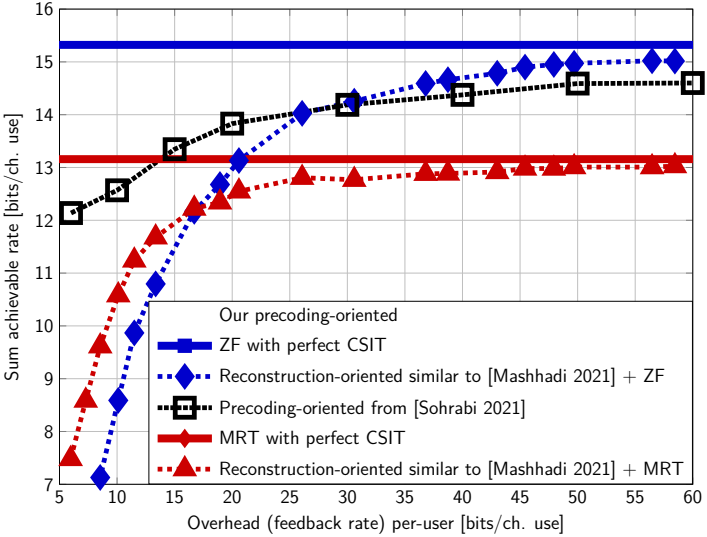

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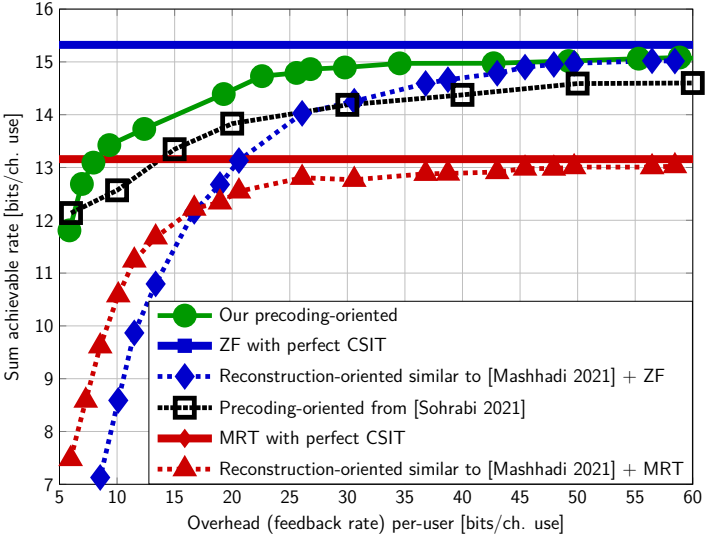

Conclusion

- Analysis of the tradeoff between feedback overhead, system performance, and channel reconstruction
- Focus on performance as the final metric for our task (MIMO precoding)
- Precoding-oriented works best for the small overhead regime
  - Optimized for overhead-performance
  - Good news for beyond 5G! Precoding-oriented may unlock the potential of *extreme* massive MIMO arrays
  - Moreover: integration with ML/AI is on the table for the next 3GPP releases
- If the feedback overhead budget is large, then all methods are equivalent

Thank you! Q&A?

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https://fabriziocarpi.github.io/

References

[1] F. Sohrabi, K. M. Attiah, and W. Yu, "Deep learning for distributed channel feedback and multiuser precoding in FDD massive MIMO," *IEEE Transactions on Wireless Communications*, vol. 20, no. 7, pp. 4044–4057, 2021.

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Simulation setup

Channel model: multipath, BS with uniform linear array.

Compare with:

- MRT/ZF with CSIT: full CSI $\mathbf{H}$ is available at the transmitter (BS), then compute maximal-ratio transmission (maximize per-user received power) or zero-forcing (minimize inter-user interference)
- Precoder-oriented from [1]: similar setup, but with a different feedback overhead optimization. The loss function is the performance and the feedback overhead is determined by the number of feedback taps (fixed).
- Reconstruction-oriented similar to [2] + MRT/ZF: system trained for overhead-distortion loss, followed by MRT/ZF (non precoding-oriented)