Neural-Network Optimized 1-bit Precoding for Massive MU-MIMO

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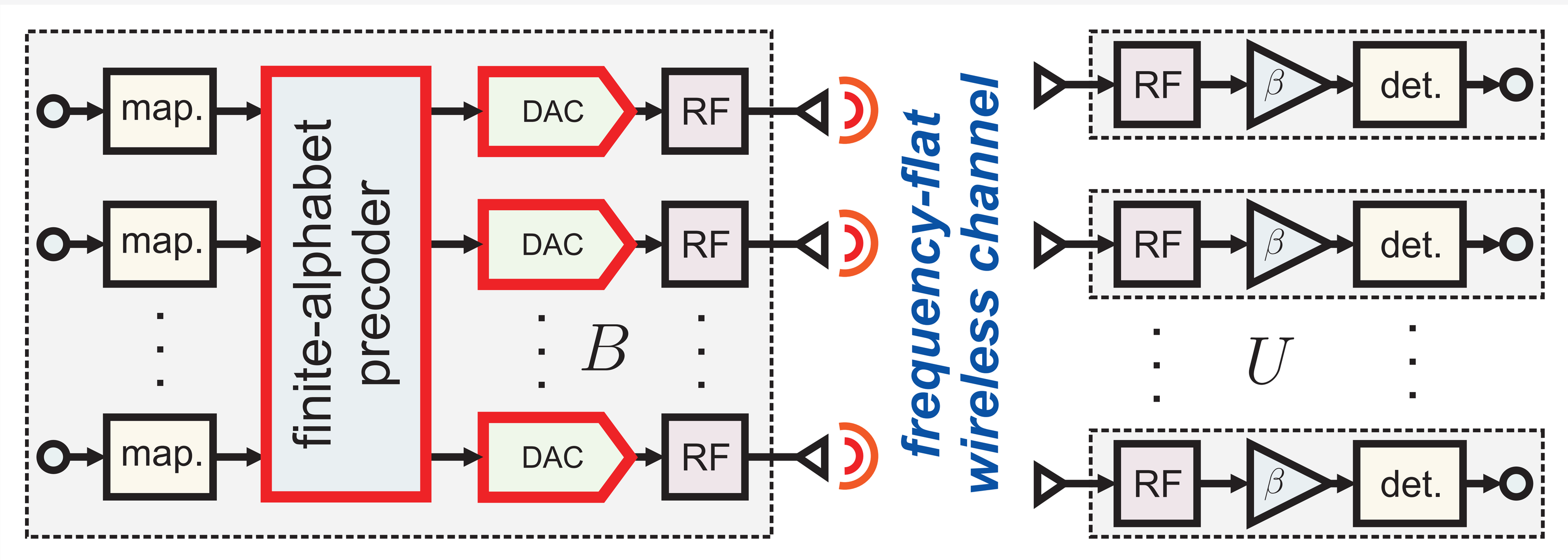
Low-Precision Massive MU-MIMO

- Massive MU-MIMO with hundreds of antennas permits communication with tens of UEs in the same time-frequency resource using **fine-grained beamforming**.
- **Prohibitively high** system costs, power consumption, and interconnect bandwidth between the BB unit and radios.
- **Low-precision DACs** can greatly reduce these costs!



MU-MIMO with 1-bit Precoding

- Standard MIMO system model: $\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$
- The precoder maps a symbol vector $\mathbf{s} = [s_1, \dots, s_U]^T \in \mathcal{O}^U$ to a precoded vector $\mathbf{x} \in \mathcal{X}^B$, where $\mathcal{X} = \{\pm\xi \pm j\xi\}$, where $\xi = \sqrt{\frac{P}{2B}}$ to satisfy a power constraint.
- The **MSE-optimal** 1-bit precoder is given by:

$$\{\hat{\mathbf{x}}, \hat{\beta}\} = \underset{\mathbf{x}\in\mathcal{X}^B,\, \beta\in\mathbb{C}}{\text{arg min}} \ \|\mathbf{s} - \beta\mathbf{H}\mathbf{x}\|_2^2 + |\beta|^2 U N_0.$$

NP-hard optimization problem!

C2PO: Biconvex 1-bit Precoding

- Let $\mathbf{A} = \left(\mathbf{I}_U - \mathbf{s}\mathbf{s}^H/\|\mathbf{s}\|_2^2\right)\mathbf{H}$. **Relaxed** precoding problem:

$$\hat{\mathbf{x}} = \underset{\mathbf{x}\in\mathcal{B}^B}{\text{arg min}} \ \tfrac{1}{2}\|\mathbf{A}\mathbf{x}\|_2^2 - \tfrac{\delta}{2}\|\mathbf{x}\|_2^2.$$

- Let $\rho = \frac{1}{1-\tau\delta}$ and $\text{prox}_g(\mathbf{z};\rho,\xi) = \text{clip}(\rho\Re\{\mathbf{z}\},\xi) + j\,\text{clip}(\rho\Im\{\mathbf{z}\},\xi)$.
- C2PO algorithm via forward-backward splitting [1]:

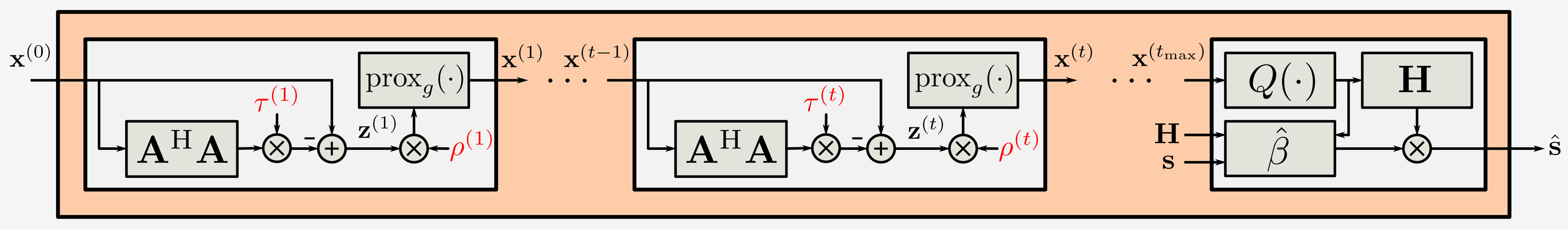
Algorithm 1 (C2PO). *Initialize* $\mathbf{x}^{(0)} = \mathbf{H}^H\mathbf{s}$. *Fix* $\tau^{(t)}$ *and* $\rho^{(t)}$. *For every iteration* $t = 1, 2, \dots, t_{max}$ *compute:*

$$\mathbf{z}^{(t)} = \mathbf{x}^{(t-1)} - \tau^{(t)}\mathbf{A}^H\mathbf{A}\mathbf{x}^{(t-1)},$$
$$\mathbf{x}^{(t)} = \text{prox}_g(\mathbf{z}^{(t)}; \rho^{(t)}, \xi).$$

Finally, quantize the output $\mathbf{x}^{(t_{max})}$ *to the set* $\mathcal{X}^B$.

Neural-Network Optimized C2PO

- **Main idea:** unfold iterations of C2PO and learn per-iteration parameters $\tau^{(t)}$ and $\rho^{(t)}$ with standard toolboxes [2].

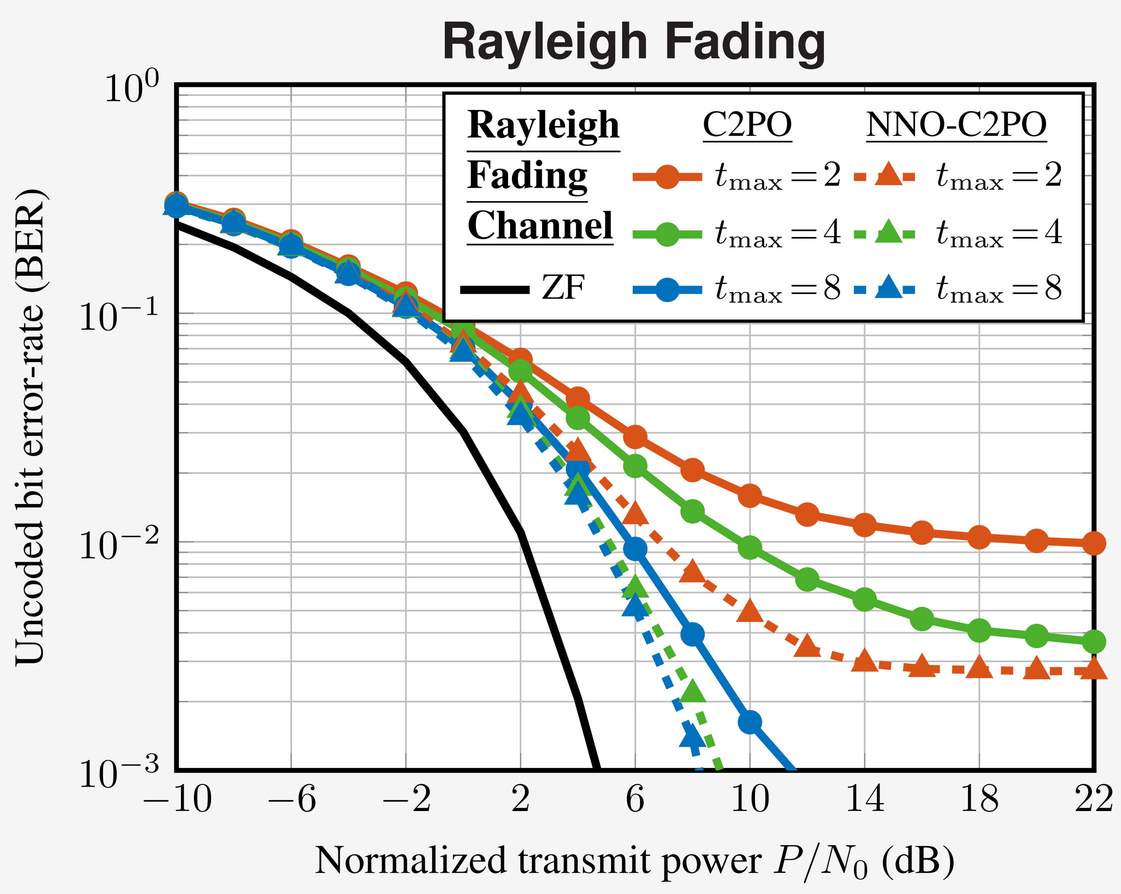


Implementation considerations:

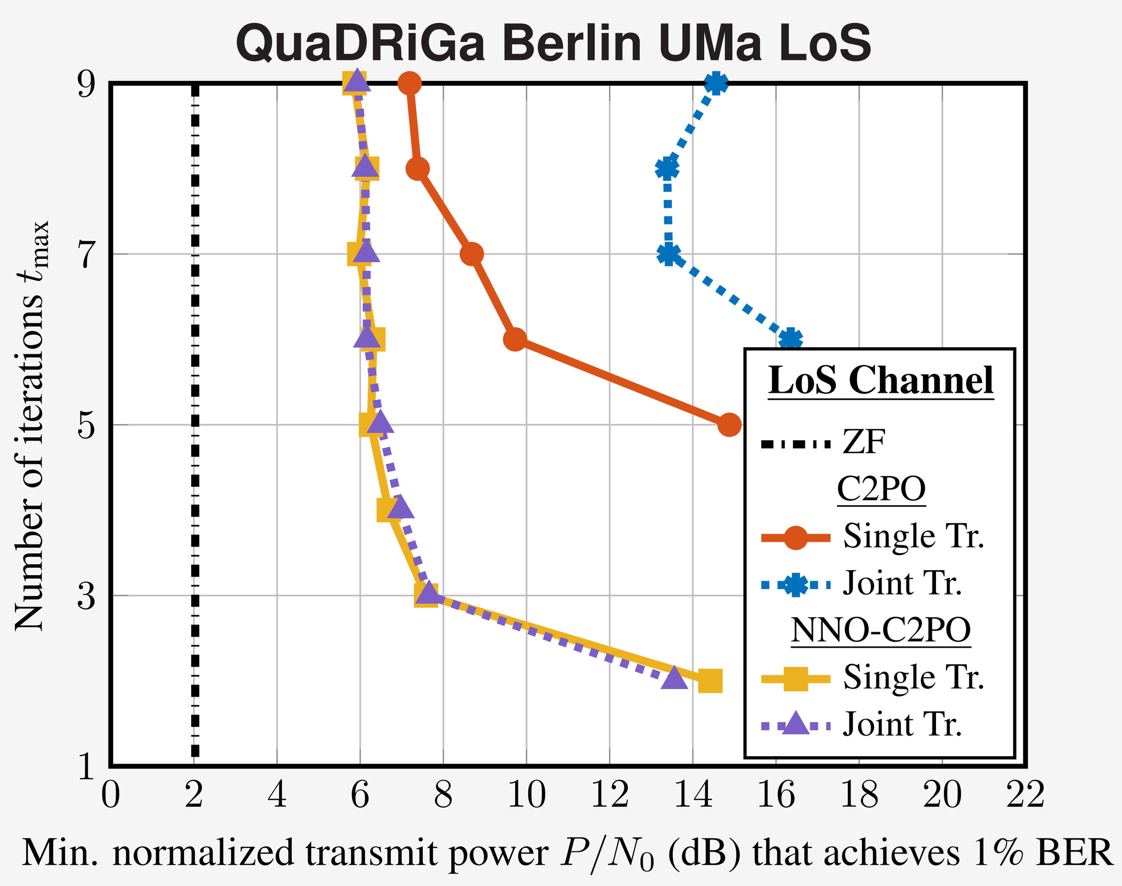
- Quantization function $Q(\cdot)$ is not differentiable, replace with **clipping function** for backpropagation.
- Real-valued equivalent C2PO formulation.
- Initialize $\tau^{(t)}$ and $\rho^{(t)}$ with known good values to speed up training and diminish effect of vanishing gradients.

Results

- All results are for $B = 128$ BS antennas, $U = 8$ UEs, 16-QAM.
- Training with 500 samples, evaluation with 1000 samples.



Identical performance, $2\times$ lower complexity!



Robustness to varying channel models!

References

[1] O. Castañeda, S. Jacobsson, G. Durisi, M. Coldrey, T. Goldstein, and C. Studer, "1-bit massive MU-MIMO precoding in VLSI," IEEE JETCAS, Dec. 2017.

[2] A. Balatsoukas-Stimming and C. Studer, "Deep Unfolding for Communications Systems: A Survey and Some New Directions," IEEE SiPS, Oct. 2019.

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