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Reconsidering Linear Transmit Signal Processing in 1-Bit Quantized Multi-User MISO Systems - Oliver De Candido et al.

Goal

- To investigate a coarsely quantized MU-MISO downlink (DL) communication system with 1-bit DACs at the base station

Contributions

- Analysis of the optimality of two aspects of traditional signal processing in 1-bit quantized MU-MISO DL systems
  - Proper signaling
  - Channel rank transmit covariance matrices
- Achievable rate analysis based on Bussgang decomposition to investigate the sum-rate lower bound
- Design of a higher-rank linear precoder based on gradient-projection algorithm

System Model

- DL scenario of a single-cell coarsely quantized MU-MISO system.
- N_t transmit antennas each equipped with two 1-bit DACs for the I and Q components
- ADCs at the K users have infinite quantization resolution
- Real valued baseband received signals

$$\bar{\boldsymbol{y}} = \bar{\boldsymbol{H}}^{\mathrm{T}} \tilde{\boldsymbol{D}} \bar{\boldsymbol{t}} + \bar{\boldsymbol{\eta}} \in \mathbb{R}^{2K}.$$

Bussgang Decomposition

- Bussgang theorem: Cross correlation between two Gaussian distributed input signals remains the same when one signal is subjected to non-linear distortion except for a scaling factor
- Non-linear function with Gaussian inputs can be modeled by a linear transformation and the addition of some distortion which is uncorrelated with the inputs
- Quantization function modeled as:

$$\bar{\boldsymbol{t}} = \mathcal{Q}_t(\bar{\boldsymbol{x}}) = \boldsymbol{A}\bar{\boldsymbol{x}} + \boldsymbol{q},$$

  where the quantization error $\mathbf{q}$ is uncorrleated with the input signal $\bar{\boldsymbol{x}}$, and the matrix $\boldsymbol{A} = \boldsymbol{R}_{\bar{t}\bar{x}}\boldsymbol{R}_{\bar{x}}^{-1}$
- Price's theorem used to compute $\boldsymbol{A}$
- Real valued received signal using the Bussgang decomposition is written as:

$$\bar{\boldsymbol{y}}_k = \bar{\boldsymbol{H}}_k^{\mathsf{T}}(\boldsymbol{A}\bar{\boldsymbol{x}} + \boldsymbol{q}) + \bar{\boldsymbol{\eta}}_k = \bar{\boldsymbol{H}}_{\mathrm{eff},k}^{\mathsf{T}}\bar{\boldsymbol{x}} + \tilde{\boldsymbol{\eta}}_k,$$

- To optimize the transmit covariance matrices to maximize the sum rate lower-bound

$$\boldsymbol{R}_{\bar{x}_{k,\mathrm{opt}}} = \underset{\boldsymbol{R}_{\bar{x}_k} \succeq \mathbf{0}, \forall k}{\arg\max} \frac{1}{2}\sum_{k=1}^{K} \mathrm{E}\left[\log_2 \det(\boldsymbol{I}_2 + \mathsf{SQINR}_k(\boldsymbol{R}_{\bar{x}}))\right],$$

- By Cholesky decomposition of the transmit covariance matrix, we get the optimization problem as

$$\boldsymbol{L}_{k,\mathrm{opt}}(\mathcal{R}_k) = \underset{\boldsymbol{L}_k(\mathcal{R}_k), \forall k}{\arg\max} \frac{1}{2}\sum_{k=1}^{K} \mathrm{E}\left[\log_2 \det(\boldsymbol{I}_2 + \mathsf{SQINR}_k(\boldsymbol{L}_k))\right],$$

- Simulation results showing the ergodic sum rate for different values of $\mathcal{R}_k$ (number of streams of each user)
- For a rank-1 channel, the ergodic sum-rate performance increases when the rank of the user's transmit covariance matrix is greater than 1
- At low-SNR, optimized transmit covariance matrices converge to those employing tradition signal processing techniques (ZF, MMSE, MF precoders)
- Linear precoder design

Gaussian Message Passing for Overloaded Massive MIMO-NOMA - Lei Liu et al.

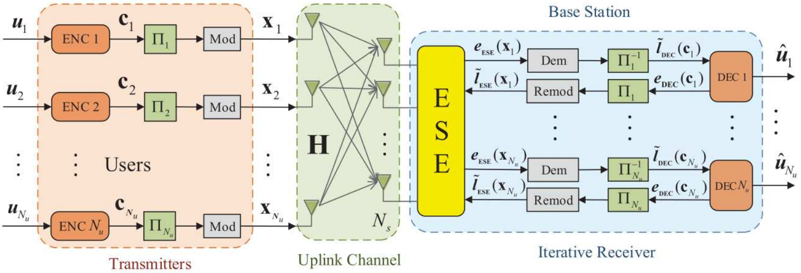
Goal

- Low complexity Gaussian message passing (GMP) multiuser detection (MUD) scheme for a coded massive MIMO overloaded system with NOMA

Contributions

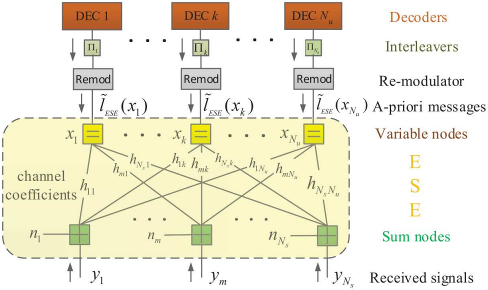
- Convergence analysis of GMP for the overloaded massive MIMO-NOMA system
- New GMP detector called scale-and-add GMP (SA-GMP), which converges to the LMMSE detection, and has a faster convergence speed than GMP

System Model



The $N_s \times 1$ received signal is given as

$$\mathbf{y}_t = \mathbf{H}\mathbf{x}_t^{tr} + \mathbf{n}_t,$$



(a) Factor Graph

Algorithm 1 GMP Algorithm

1: **Input:** $\bar{\mathbf{x}}^l$, $\bar{\mathbf{v}}_{\mathbf{x}}^l$, σ_n^2, $\epsilon > 0$, N_{ite}^{ese}, $\mathbf{H}$ and calculate $\mathbf{H}^{(2)}$.
2: **Initialization:** $\tau = 0$, $\mathbf{X}_{us}(0) = \mathbf{0}$, $\mathbf{V}_{us}(0) = +\infty$.
3: **Do**
4: $\tau = \tau + 1$,
5: $\widetilde{\mathbf{X}}_{us}(\tau) = \mathbf{X}_{us}(\tau).*\mathbf{H}^T$ and $\widetilde{\mathbf{V}}_{us}(\tau) = \mathbf{V}_{us}(\tau).*\mathbf{H}^{(2)^T}$,
6:
$$\begin{bmatrix}\mathbf{X}_{su}(\tau)\\ \mathbf{V}_{su}(\tau)\end{bmatrix} = \begin{bmatrix}\mathbf{y} - diag^{-1}\{\mathbf{1}_{M\times K}\cdot\widetilde{\mathbf{X}}_{us}(\tau-1)\}\\ \sigma_n^2\mathbf{1}_{M\times 1} + diag^{-1}\{\mathbf{1}_{M\times K}\cdot\widetilde{\mathbf{V}}_{us}(\tau-1)\}\end{bmatrix}\cdot\mathbf{1}_{1\times K},$$
7:
$$\widetilde{\mathbf{W}}_{su}(\tau) = \mathbf{H}^{(2)}.*\mathbf{V}_{su}^{(-1)}(\tau),$$
$$\widetilde{\mathbf{G}}_{su}(\tau) = \mathbf{H}.*\mathbf{V}_{su}^{(-1)}(\tau).*\mathbf{X}_{su}(\tau),$$
8:
$$\begin{bmatrix}\mathbf{W}_{us}(\tau)\\ \mathbf{G}_{us}(\tau)\end{bmatrix} = \begin{bmatrix}\bar{\mathbf{v}}_{\mathbf{x}}^{l(-1)} + diag^{-1}\left\{\mathbf{1}\cdot\widetilde{\mathbf{W}}_{su}(\tau)\right\}\\ \bar{\mathbf{v}}_{\mathbf{x}}^{l(-1)}.*\bar{\mathbf{x}}^l + diag^{-1}\left\{\mathbf{1}\cdot\widetilde{\mathbf{G}}_{su}(\tau)\right\}\end{bmatrix}\cdot\mathbf{1} - \begin{bmatrix}\widetilde{\mathbf{W}}_{su}^T(\tau)\\ \widetilde{\mathbf{G}}_{su}^T(\tau)\end{bmatrix},$$
9: $\mathbf{V}_{us}(\tau) = \mathbf{W}_{us}^{(-1)}(\tau)$ and $\mathbf{X}_{us}(\tau) = \mathbf{V}_{us}(\tau).*\mathbf{G}_{us}(\tau)$.
10: **While** $(|\mathbf{E}_{us}(\tau) - \mathbf{E}_{us}(\tau-1)| > \epsilon$ **or** $\tau \le N_{ite}^{ese})$
11:
$$\bar{\mathbf{v}}^e = \left(diag^{-1}\left\{\mathbf{1}_{K\times M}\cdot\widetilde{\mathbf{W}}_{su}(\tau)\right\}\right)^{(-1)},$$
$$\bar{\mathbf{x}}^e = \bar{\mathbf{v}}^e.*diag^{-1}\left\{\mathbf{1}_{K\times M}\cdot\widetilde{\mathbf{G}}_{su}(\tau)\right\}.$$
12: **Output:** $\bar{\mathbf{x}}^e$ and $\bar{\mathbf{v}}^e$.

(b) GMP Algorithm

Variance Convergence of GMP

Proposition

In the massive MIMO-NOMA, where $\beta = N_u/N_s$ is fixed, N_u is large, and $\mathbf{V}_{\underline{\mathbf{x}}}^{l} = \overline{v}^{l}\mathbf{I}_{N_u}$, the a-posteriori variances of GMP converge to

$$\hat{v}_i \approx v_{i\to m}^{u}(\infty) = \hat{v} = MSE^{GMP}$$
$$= \frac{\sqrt{(snr^{-1}+N_s-N_u)^2+4N_u snr^{-1}}-(snr^{-1}+N_s-N_u)}{2N_u\overline{v}^{l^{-1}}}$$

where $i \in \mathcal{N}_u, m \in \mathcal{N}_s$, and $snr = \overline{v}^{l}/\sigma_n^2$ is the signal to noise ratio.

Theorem

In the massive MIMO-NOMA, where $\beta = N_u/N_s$ is fixed, N_u is large, and $\mathbf{V}_{\underline{\mathbf{x}}}^{l} = \overline{v}^{l}\mathbf{I}_{N_u}$, the variances of GMP converge to that of the LMMSE detector.

Mean Convergence of GMP

Theorem

In the overloaded massive MIMO-NOMA where $\beta = N_u/N_s$ is fixed, N_u is large, and $\mathbf{V}_{\mathbf{x}}^{l} = \overline{v}^{l}\mathbf{I}_{N_u}$, the GMP converges to

$$\hat{\mathbf{x}} = \left(\theta\mathbf{H}^T\mathbf{H} + \mathbf{I}_{N_u}\right)^{-1}\left(\theta\mathbf{H}^T\mathbf{y} + \alpha\bar{\mathbf{x}}^{l}\right),$$

where $\theta = \hat{v}/\sigma_n^2$ and $\alpha = \hat{v}/v^{l}$, if any of the following conditions holds.

1. *The matrix $\mathbf{I}_{N_s} + \gamma(\mathbf{H}\mathbf{H}^T - \mathbf{D}_{\mathbf{H}\mathbf{H}^T})$ is strictly or irreducibly diagonally dominant.*
2. $\rho(\gamma(\mathbf{H}\mathbf{H}^T - \mathbf{D}_{\mathbf{H}\mathbf{H}^T})) < 1$, *where $\gamma = \hat{v}/v^{s}$.*

Using random matrix theory results, we have

$$\rho_{GMP} = \rho(\gamma(\mathbf{H}\mathbf{H}^T - \mathbf{D}_{\mathbf{H}\mathbf{H}^T})) \to \gamma N_u(\beta^{-1} + 2\sqrt{\beta^{-1}}) = \gamma(N_s + 2\sqrt{N_s N_u}).$$

Corollary

In the overloaded massive MIMO-NOMA where $\beta = N_u/N_s$ is fixed, N_u is large, and $\mathbf{V}_{\mathbf{x}}^{l} = \overline{v}^{l}\mathbf{I}_{N_u}$, the spectral radius is given by

$$\rho_{GMP} = \gamma(N_s + 2\sqrt{N_s N_u}).$$

If $\beta > (\sqrt{(2) - 1})^{-2}$, the GMP converges to

$$\hat{\mathbf{x}} = \left(\theta\mathbf{H}^T\mathbf{H} + I_{N_u}\right)^{-1}\left(\theta\mathbf{H}^T\mathbf{y} + \alpha\bar{\mathbf{x}}^{l}\right), \tag{18}$$

Multi-Cell Multi-User Massive FD-MIMO: Downlink Precoding and Throughput Analysis

Contributions

- Unitary ESPRIT-based uplink DoA estimation method for multi-cell multi-user mm-wave massive FD-MIMO OFDM network
  - Non orthogonal spreading sequences (length Q) are used as UL pilots
  - Characterized the MSE of unitary ESPRIT-based UL DoA estimation
- Derived the sum-rate maximizing DL precoding and power allocation strategy for the FD-MIMO system
  - Large antenna array regime analysis for DL precoding and optimal power allocation under both perfect and imperfect DoA estimation scenarios

System Model

- Uplink (UL):
  - N_t transmit antennas, N_r receive antennas at each base station (BS)
  - $N_r \times Q$ frequency domain received signal for the k^{th} subcarrier at the i^{th} BS can be written as

$$\mathbf{Z}_i(k) = \sum_{g=0}^{G-1} \sum_{j=0}^{J-1} \sqrt{\Lambda_{jg,i}} \mathbf{H}_{jg,i}(k) \mathbf{X}_{jg}(k) + \mathbf{W}_i(k),$$

  - Geometric channel model for mm-wave frequencies

$$\mathbf{C}_{jg,i}(\ell) = \sum_{p=0}^{P_{jg,i,\ell}-1} \alpha_{jg,i}(\ell, p) \mathbf{e}_{r,jg,i}(\ell, p) \mathbf{e}^H_{t,jg,i}(\ell, p),$$

  - 1-D ULA at the users and 2-D UPA at the BS

- Downlink (DL): Received signal at the n^{th} MS in the i^{th} cell can be written as

$$\mathbf{y}_{ni}^{dl}[k] = \sum_{g=0}^{G-1}\sum_{j=0}^{J-1}\sqrt{\Lambda_{ni,g}}\mathbf{H}_{ni,g}^{dl}[k]\mathbf{V}_{jg}[k]\mathbf{s}_{jg}^{dl}[k] + \mathbf{n}_{ni}^{dl}[k]$$

$$= \sqrt{\Lambda_{ni,i}}\mathbf{H}_{ni,i}^{dl}[k]\mathbf{V}_{ni}[k]\mathbf{s}_{ni}^{dl}[k] + \sum_{\substack{j=0\\ j\neq n}}^{J-1}\sqrt{\Lambda_{ni,i}}\mathbf{H}_{ni,i}^{dl}[k]\mathbf{V}_{ji}[k]\mathbf{s}_{ji}^{dl}[k]$$

$$+ \sum_{\substack{g=0\\ g\neq i}}^{G-1}\sum_{\substack{j=0\\ j\neq n}}^{J-1}\sqrt{\Lambda_{ni,g}}\mathbf{H}_{ni,g}^{dl}[k]\mathbf{V}_{jg}[k]\mathbf{s}_{jg}^{dl}[k] + \mathbf{n}_{ni}^{dl}[k],$$

- Sum-rate maximization problem with a total transmit power constraint
  - Equivalent to sum-MSE minimization problem

$$\min_{\{\mathbf{V}_{ji}[k]\}} \quad \left|\left|\bar{\mathbf{D}}_{i,i}\bar{\mathbf{A}}_{i,i}^{T}[k]\mathbf{V}_{i}[k] - \mathbf{I}\right|\right|_F^2$$

$$s.t. \ \sum_{j=0}^{J-1}\mathrm{Tr}\left(\mathbf{V}_{ji}[k]\mathbf{V}_{ji}[k]^H\right) \leq P_t,$$

Other Interesting Papers

1. Sub-System SVD Hybrid Beamforming Design for Millimeter Wave Multi-Carrier Systems
2. Fog Massive MIMO: A User-Centric Seamless Hot-Spot Architecture
3. Asymptotic Performance Analysis of GSVD-NOMA Systems With a Large-Scale Antenna Array
4. Multi-User Analog Beamforming in Millimeter Wave MIMO Systems Based on Path Angle Information
5. Pilot- and CP-Aided Channel Estimation in MIMO Non-Orthogonal Multi-Carriers
6. Throughput Maximization for Delay-Sensitive Random Access Communication
7. Revisiting the MIMO Capacity With Per-Antenna Power Constraint: Fixed-Point Iteration and Alternating Optimization
8. Message-Passing Receiver Design for Joint Channel Estimation and Data Decoding in Uplink Grant-Free SCMA Systems
9. FDD Massive MIMO via UL/DL Channel Covariance Extrapolation and Active Channel Sparsification