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# Relay-Aided Space-Time Beamforming for Interference Networks with Partial Channel Knowledge

- Contributions
  - Proposes a novel multiantenna interference management technique referred to as r-STBF.
  - $\frac{KM}{K+M-1}$ multiplexing gain is achievable in a K-user MISO interference channel when the relay has $M$ antennas.
  - $\frac{KL}{K+L-1}$ multiplexing gain is achievable in a $K \times L$ SISO $X$ channel with an $M$ antenna relay.
- System Model
  - MIMO Relay-Aided $K$-User MISO Interference Channel
  - Assumption: Local CSI at the Rx, Delayed CSI at the relay, CSI of the relay to receiver using channel reciprocity.

$$y^{[k]}(n) = \mathbf{h}^{[k,k]}(n)\mathbf{x}^{[k]}(n) + \sum_{j=1, j\neq k}^{K} \mathbf{h}^{[k,j]T}(n)\mathbf{x}^{[j]}(n) + \mathbf{h}^{[k,R]}(n)\mathbf{x}^{[R]}(n) + z^{[k]}(n) \quad (1)$$

$$\mathbf{y}^{[R]}(n) = \sum_{k=1}^{K} \mathbf{H}^{[R,k]}(n)\mathbf{x}^{[k]}(n) + \mathbf{z}^{[R]}(n), k \in \mathcal{K}. \quad (2)$$

- r-STBF explained in the next slide using a toy example ($K = M = 2$).

**r-STBF**: **Phase 1** (2 time slots): Side-Information Learning: Only transmitters transmit and relay receives. Received signals at the users 1 and 2.

$$\mathcal{L}^{[1,1]}(1) = h_1^{[1,1]}(1)s_1^{[1]} + h_2^{[1,1]}(1)s_2^{[1]} \quad (3)$$
$$\mathcal{L}^{[2,1]}(1) = h_1^{[2,1]}(1)s_1^{[1]} + h_2^{[2,1]}(1)s_2^{[1]} \quad (4)$$
$$\mathcal{L}^{[1,2]}(2) = h_1^{[1,2]}(2)s_1^{[2]} + h_2^{[1,2]}(2)s_2^{[2]} \quad (5)$$
$$\mathcal{L}^{[2,2]}(2) = h_1^{[1,1]}(2)s_1^{[2]} + h_2^{[2,2]}(2)s_2^{[2]} \quad (6)$$
$$(7)$$

Receive beamforming used at the relay to separate the two received symbols in time slot $k$.

$$\hat{\mathbf{s}}^{[k]} = \left(\mathbf{H}^{[R,k]}(k)\right)^{-1}\mathbf{y}^{[R]}(k) = \mathbf{s}^{[k]} + \left(\mathbf{H}^{[R,k]}(k)\right)^{-1}\mathbf{z}^{[R]}(k) \quad (8)$$
$$k \in 1, 2, \text{where } \mathbf{s}^{[k]} = [s_1^{[k]}, s_2^{[k]}]^T \quad (9)$$

**Phase 2** (1 time slot): Space-Time Relay Transmission: Relay forwards the received signals by applying space-time relay beamforming.

$$\begin{aligned}\mathbf{x}^{[R]}(3) &= \gamma\left(\mathbf{V}^{[1]}\hat{\mathbf{s}}^{[1]} + \mathbf{V}^{[2]}\hat{\mathbf{s}}^{[2]}\right)\\ &= \gamma\mathbf{V}^{[1]}\mathbf{s}^{[1]} + \gamma\mathbf{V}^{[2]}\mathbf{s}^{[2]} + \gamma\mathbf{z}^{[R]}\end{aligned} \quad (10)$$

Beamforming: $\mathbf{V}^{[1]}$ and $\mathbf{V}^{[2]}$ designed such that

$$\gamma\mathbf{h}^{[2,R]T}(3)\mathbf{V}^{[1]} = \mathbf{h}^{[2,1]T}(1), \qquad \mathbf{h}^{[2,R]T}(3)\mathbf{V}^{[2]} = \left[-h_2^{[2,2]*}(2), h_1^{[2,2]*}(2)\right] \quad (11)$$
$$\gamma\mathbf{h}^{[1,R]T}(3)\mathbf{V}^{[2]} = \mathbf{h}^{[1,2]T}(2), \qquad \mathbf{h}^{[1,R]T}(3)\mathbf{V}^{[1]} = \left[-h_2^{[1,1]*}(1), h_1^{[1,1]*}(1)\right] \quad (12)$$

# PRIME: Phase Retrieval via Majorization-Minimization

- Contributions
  - Proposed low-complexity algorithms for phase retrieval based on MM framework.
  - Three algorithms: PRIME-Modulus-Single-Term, PRIME-Modulus-Both-Terms, PRIME-Power.
- Optimization Problem 1:

$$\underset{\mathbf{x}}{\text{minimize}} \sum_{i=1}^{N} \left| y_i - |\mathbf{a}_i^H \mathbf{x}|^2 \right|_2^2 = \underset{\mathbf{x}}{\text{minimize}} \left\| \mathbf{y} - |\mathbf{A}^H \mathbf{x}|^2 \right\|_2^2 \tag{13}$$

- Optimization Problem 2:

$$\underset{\mathbf{x}}{\text{minimize}} \left\| \sqrt{\mathbf{y}} - |\mathbf{A}^H \mathbf{x}| \right\|_2^2 \tag{14}$$

$$= \underset{\mathbf{x}}{\text{minimize}} \sum_{i=1}^{N} \left( \left| \mathbf{a}_i^H \mathbf{x} \right|^2 - 2\sqrt{y_i} \left| \mathbf{a}_i^H \mathbf{x} \right| + y_i \right) \tag{15}$$

$\mathbf{A} \in \mathbb{C}^{K \times N}$ is the measurement matrix,
$\mathbf{y} \in \mathbb{R}^{N \times 1}$ is the measurement vector,
$\mathbf{x} \in \mathbb{C}^{K \times 1}$ is the complex vector to be estimated.

- PRIME-Modulus-Single-Term: To solve problem 2. Majorization of the non-convex second term using Cauchy-Schwarz inequality, which leads to a simple least squares problem:

$$\left|\mathbf{a}_i^H\mathbf{x}\right| . \left|\mathbf{a}_i^H\mathbf{x}^{(k)}\right| \geq \text{Re}\left(\left|\mathbf{a}_i^H\mathbf{x}\right|\left(\mathbf{x}^{(k)}\right)^H\mathbf{a}_i\right) \tag{16}$$

- PRIME-Modulus-Both-Terms: To solve problem 2. Majorization of both the terms (for $2^{\text{nd}}$, similar to the first algorithm). For the first term, the following result is used.

$$\mathbf{x}^H\mathbf{L}\mathbf{x} \geq \mathbf{x}^H\mathbf{M}\mathbf{x} + 2\text{Re}\left(\mathbf{x}^H(\mathbf{L}-\mathbf{M})\mathbf{x}_0\right) + \mathbf{x}_0^H(\mathbf{M}-\mathbf{L})\mathbf{x}_0 \tag{17}$$

where $\mathbf{M}$ and $\mathbf{L}$ are Hermitian matrices such that $\mathbf{M} \succeq \mathbf{L}$.
- PRIME-Power: To solve problem 1. Majorization of problem 1 as a leading eigenvector problem using MM techniques.

$$\underset{\mathbf{x},\mathbf{X}}{\text{minimize}} \sum_{i=1}^{N}\left(y_i - Tr\left(\mathbf{A}_i\mathbf{X}\right)\right)^2 \tag{18}$$

$$= \underset{\mathbf{x},\mathbf{X}}{\text{minimize}} \underbrace{\sum_{i=1}^{N}\left(Tr(\mathbf{A}_i\mathbf{X})\right)^2}_{vec(\mathbf{X})^H\mathbf{\Phi}vec(\mathbf{X})} - \sum_{i=1}^{N}2y_i Tr(\mathbf{A}_i\mathbf{X}) \tag{19}$$

$$\text{subject to} \quad \mathbf{X} = \mathbf{x}\mathbf{x}^H$$

where $\mathbf{A}_i = \mathbf{a}_i\mathbf{a}_i^H$, $\mathbf{X} = \mathbf{x}\mathbf{x}^H$ and $\mathbf{\Phi} \triangleq \sum_{i=1}^{N} vec(\mathbf{A}_i)vec(\mathbf{A}_i)^H$.

# MAP Support Detection for Greedy Sparse Signal Recovery Algorithms in Compressive Sensing

- Contributions
  - Proposed a novel support detection method for greedy algorithms, referred to as MAP support detection.
  - Algorithms: MAP-MP, MAP-OMP, MAP-gOMP, MAP-CoSaMP, MAP-SP.
- System Model:

$$\mathbf{y} = \mathbf{\Phi x} + \mathbf{w} \tag{20}$$

where $\mathbf{\Phi} \in \mathbb{R}^{M \times N} = [\mathbf{a}_1, ..., \mathbf{a}_N]$, $\mathbf{y} \in \mathbb{R}^M$ is the measurement vector, $\mathbf{x} \in \mathbb{R}^N$ is the vector to be estimated, $\mathbf{w} \in \mathbb{R}^M$ is the Gaussian noise with zero mean and variance $\sigma_w^2$.

- The entries of the dictionary matrix are drawn from an IID Gaussian distribution with zero mean and variance $\frac{1}{M}$.
- Sparsity level $K$ is known apriori.

- $\mathbf{x} \in \{0,1\}^N$, residual vector in $k^{th}$ iteration is $\mathbf{r}^{k-1}$. Estimated support in the $k^{th}$ iteration is $S^{k-1}$.

$$z_n^k = \frac{\mathbf{a}_n^T}{\|\mathbf{a}_n\|_2} \overbrace{\left( \sum_{l \in \mathcal{T} \setminus S^{k-1}} \mathbf{a}_l x_l + \mathbf{w} \right)}^{\mathbf{r}^{k-1}} \tag{21}$$

$$= \|\mathbf{a}_n\|_2 x_n + \sum_{l \in \mathcal{T} \setminus \{S^{k-1} \cup \{n\}\}} \frac{\mathbf{a}_n^T \mathbf{a}_l x_l}{\|\mathbf{a}_n\|_2} + \frac{\mathbf{a}_n^T \mathbf{w}}{\|\mathbf{a}_n\|_2} \tag{22}$$

- Hypothesis test corresponding to $x_n = 0$ and $x_n = 1$:

$$\mathcal{H}_0 : z_n^k = \sum_{l \in \mathcal{T} \setminus \{S^{k-1} \cup \{n\}\}} \frac{\mathbf{a}_n^T \mathbf{a}_l x_l}{\|\mathbf{a}_n\|_2} + \frac{\mathbf{a}_n^T \mathbf{w}}{\|\mathbf{a}_n\|_2} \tag{23}$$

$$\mathcal{H}_1 : z_n^k = \|\mathbf{a}_n\|_2 x_n + \sum_{l \in \mathcal{T} \setminus \{S^{k-1} \cup \{n\}\}} \frac{\mathbf{a}_n^T \mathbf{a}_l x_l}{\|\mathbf{a}_n\|_2} + \frac{\mathbf{a}_n^T \mathbf{w}}{\|\mathbf{a}_n\|_2} \tag{24}$$

- Conditional probability density functions of $z_n^k$ given $x_n$ is used to determine the MAP ratio for a given observation $z_n^k$. The support index is determined by selecting the index which maximizes the MAP ratio.

# Delay Control for Temporally Fair Scheduling Policies via Opportunistic Mixing

- Contributions
  - Proposed a novel concept of scheduling policy for delay control.
  - Developed a high performance, flexible delay control framework with a set of algorithms that can equip any temporally fair scheduling policy with a highly effective delay control capability.
- System Model:
  - Wireless system with $K$ users competing for a single frequency resource. Time is divided into equal slots.
  - Channel metric $x_k$, utility function for selecting users $u_k = U_k(x_k)$, service time $\tau_k$
- Algorithms:
  - Delay control via Markov decision process (MDP).
  - Delay control via round robin mixing (RRM).
  - Delay control via opportunistic Bernoulli mixing (OBM).

Other Interesting Papers

- Exploring algorithmic limits of matrix rank minimization under affine constraints.
- Multivariate fronthaul quantization for downlink C-RAN.
- Exact joint sparse frequency recovery via optimization methods.
- Design and performance analysis of noncoherent detection systems with massive receiver arrays.
- Newtonized orthogonal matching pursuit: frequency estimation over the continuum.
- Recursive identification method for piecewise ARX models: a sparse estimation approach.
- Design and analysis of broadband amplify-and-forward cooperative systems: a fractionally-spaced sampling approach.