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Exploiting Spatial Channel Covariance for Hybrid Precoding in Massive MIMO Systems

Goal:

- To propose a new hybrid precoding technique for massive MIMO systems using spatial channel covariance matrices

System Model:

- Base station with N antennas, M RF chains. U users with single antenna

$$\mathbf{y} = \mathbf{H}^* \mathbf{F}_{RF} \mathbf{F}_{BB} \mathbf{P} \mathbf{s} + \mathbf{n}$$

Contributions:

- Regularized zero forcing (RZF) precoding for digital precoding
- Unconstrained analog precoder design using only the users' spatial channel covariance matrices
- Divide the unconstrained analog precoder into two separate matrices:
  - Constrained analog precoding matrix
  - Additional baseband precoding matrix
- Analysis of the signal-to-leakage-plus-noise ratio (SLNR) loss caused by the hybrid precoding

- Hybrid Precoding using Spatial Channel Covariance Matrices:
  - RZF for digital precoding:

$$\mathbf{F}_{BB} = \left(\mathbf{F}_{RF}^{*}\mathbf{H}\mathbf{H}^{*}\mathbf{F}_{RF} + \beta\mathbf{I}\right)^{-1}\mathbf{F}_{RF}^{*}\mathbf{H}$$

  - Goal is to find $\mathbf{F}_{RF}$ to maximize the SLNR. $\mathbf{F}_{RF}$ is decomposed into product of two semi-unitary matrices.
  - As $N \to \infty$, SLNR converges to a deterministic value which depends only on the spatial channel covariance
  - Random matrix theory tools are used to obtain the optimal analog precoding matrix without phase shifter constraint
- Hybrid Precoding under Phase Shifter constraint:

$$\min_{\mathbf{F}_{RF,C}, \left|\left[\mathbf{F}_{RF,C}\right]_{i,j}\right| = \frac{1}{\sqrt{N}}, \mathbf{A}} \left\|\mathbf{F}_{RF,UC}\mathbf{A} - \mathbf{F}_{RF,C}\right\|_F^2$$

  - $\mathbf{A}$ introduced to increase the degrees of freedom in the design
  - Alternating minimization used to solve for $\mathbf{F}_{RF,C}, \mathbf{A}$
  - For maintaining the orthogonality of the unconstrained solution, a compensation matrix is introduced in the baseband
  - RZF digital precoder designed after the precompensation matrix design
- Asymptotic analysis for the SLNR loss caused by the hybrid structure

Fast Approximation Algorithms for a Class of Non-convex QCQP Problems Using First-Order Methods

Goal:

- To solve a special class of non-convex QCQP optimization problems:

$$\begin{aligned} \max_{\mathbf{x} \in \mathbb{C}^N} \quad & \min_{m \in \mathcal{M}} \mathbf{x}^H \mathbf{A}_m \mathbf{x} \\ \text{s.t.} \quad & \mathbf{x} \in \mathcal{F} \end{aligned} \tag{1}$$

where $\mathcal{M} = \{1, 2, \dots, M\}, \mathbf{A}_m \in \mathbb{C}^{N \times N} \succeq \mathbf{0}, \mathcal{F} \subseteq \mathbb{C}^N$ is a compact, convex set

Contributions:

- Proposed low complexity, high performance SCA algorithms for solving (1)
  - Fast, first order methods (FOMs) for solving each non-smooth, convex subproblem
  - Subproblem expressed as the maximization of a bilinear function over a convex set
    - Nesterov smoothing technique, Nemirovski's saddle point reformulation approach to develop FOMs to solve each SCA subproblem
  - ADMM approach
- Convergence analysis using two different techniques
  - KKT conditions of the local smooth convex problem
  - Establish the link between the first order properties of the objective and its non-smooth, convex surrogate (first time in the literature)

- SCA: Find a lower (upper) bound and maximize (minimize) the convex surrogate function iteratively
- First order Taylor series used to find a convex, non-smooth upper bound for the objective function of the reformulated problem
- Existing Approaches:
  - Eprigraph representation: High computational complexity
  - Projected subgradient methods: Slow convergence rate
- Problem structure utilized to express the problem as

$$\min_{\tilde{\mathbf{x}} \in \mathbb{R}^{2N}} \max_{\tilde{\mathbf{y}} \in \Delta_M} \phi^{(n)}(\tilde{\mathbf{x}}, \tilde{\mathbf{y}}) \quad \text{s.t.} \quad \tilde{\mathbf{x}} \in \tilde{\mathcal{F}}$$

- New approach using
  - Smoothing via conjugation - Nesterov's smoothing technique
  - Convex-concave saddle point reformulation - Nemirovski's formulation
  - ADMM

Transmit Precoding for Interference Exploitation in the Underlay Cognitive Radio Z-channel

Goal:

- To propose a Tx precoding scheme for the CR Z-channel to improve the QoS of SUs

System Model:

- Single cell CR Z-channel system, 1 N-antenna SBS, K single antenna SUs, L single antenna PUs
- Rx signal at the i^{th} SU:

$$y_i = \mathbf{h}_i^T \mathbf{x} + n_i = \underbrace{\mathbf{h}_i^T \mathbf{w}_i b_i}_{\text{desired signal}} + \underbrace{\sum_{j=1, j \neq i}^{K} \mathbf{h}_i^T \mathbf{w}_j b_j + n_i}_{\text{interference plus noise}}$$

Contributions:

- Proposed a precoder design to minimize the worst case SU's SEP (WSUSEP)
- Derived conditions to reformulate the problem to a convex problem
- Derived a computationally efficient approximation technique that achieves close to optimal performance

Conventional SINR based CR DL Beamforming design: Max-Min fair problem:

- Maximize the min SINR subj. to average interference and total Tx power constraints
- Problem reformulated to a quasi-convex optimization problem and solved using sequential SOCP

WSUSEP Approach:

- Precoder design to constructively utilize the interfering signal to enhance the desired signal
- To design the precoder to steer the rx signals of SUs into the corresponding decision regions to reduce the SEP

$$\begin{aligned} \min_{\mathbf{x},\rho} \quad & \rho \\ \text{s.t.} \quad & \Pr\left(\psi_i\left(\mathbf{x}, n_i\right) \in \mathcal{A}_{\theta}^{2\pi-\theta}\right) \le \rho, i = 1, \ldots, K, \\ & \|\mathbf{x}\|^2 \le P, \left|\mathbf{g}_l^T \mathbf{x}\right|^2 \le \epsilon_l, l = 1, \ldots, L \end{aligned} \tag{2}$$

- The above problem reformulated in which the constraint depends on the joint normal CDF of the noise
- Solved using barrier method

Goal:

- To propose a successive pseudoconvex approximation algrorithm to efficiently compute stationary points for a large class of nonconvex optimization problems given below:

$$\begin{aligned} \min_{\mathbf{x}} \quad & f(\mathbf{x}) + g(\mathbf{x}) \\ \text{s.t.} \quad & x \in \mathcal{X} \end{aligned} \tag{3}$$

where f is differentiable (convex or non convex), and g is non-differentiable and convex

Contributions:

- Developed a novel iterative pseudoconvex method to solve problem (3)
- Proposed new exact/successive line search methods to determine the step size when the objective is non-differeticable
- Applications:
  - Sum rate maximization of MIMO broadcast channel
  - Energy efficiency maximization of a massive MIMO system
  - LASSO (to illustrate the advantage of the proposed step size)

Proposed Successive Pesudoconvex Approximation Algorithm:

- In iteration t, let $\tilde{f}\left(\mathbf{x};\mathbf{x}^t\right)$ be the approximate function of $f\left(\mathbf{x}\right)$ around $\mathbf{x}^t$
- Assumptions on $\tilde{f}\left(\mathbf{x};\mathbf{x}^t\right)$: pseudoconvex, continuously differentiable, and gradient of f and $\tilde{f}$ are identical at $\mathbf{x}^t$
- Two more assumptions on the sequence $\{\mathbf{x}^t\}$ ensures that any limit point of $\{\mathbf{x}^t\}$ is a stationary point of the original problem
- Nondifferentiable optimization problems: Reformulate using auxiliary variables

$$\begin{aligned} \min_{\mathbf{x}} \quad & f\left(\mathbf{x}\right) + y \\ \text{s.t.} \quad & x \in \mathcal{X}, g\left(\mathbf{x}\right) \leq y \end{aligned} \tag{4}$$

  - Assumption: $\tilde{f}\left(\mathbf{x},\mathbf{y}\right)$ is convex
  - g replaced by auxiliary variable
  - Convexity of g and Jensen's inequality used to replace the auxiliary variables (Pg. 3317, Step 2 in the paper for more details)
  - Converges to a stationary point of f

Other Interesting Papers

July 1, 2017

1. Projected Nesterov's Proximal-Gradient Algorithm for Sparse Signal Recovery
2. Optimal Training Sequences for Large-Scale MIMO-OFDM Systems
3. (Overview Article) Tensor Decomposition for Signal Processing and Machine Learning

July 15, 2017

1. Joint Sensing Matrix and Sparsifying Dictionary Optimization for Tensor Compressive Sensing
2. Sparsity-Driven Laplacian-Regularized Outlier Identification for Dictionary Learning
3. An Information Theoretic Approach to Robust Constrained Code Design for MIMO Radars
4. An Efficient Global Algorithm for Single-Group Multicast Beamforming
5. Maximum-Likelihood Detection for MIMO Systems Based on Differential Metrics