Journal Watch
IEEE Transactions on Signal Processing, Vol. 65, No. 11, June 1, 2017

Sai Subramanyam Thoota

SPC Lab, Department of ECE
Indian Institute of Science

July 8, 2017

BDMA in Multicell Massive MIMO Communications: Power Allocation Algorithms

Goal:

- To investigate power allocation strategies for beam division multiple access transmission in multicell massive MIMO communications.

System Model:

- Multiple base stations (with multiple transmit antennas) transmitting to multiple user equipments (with multiple receive antennas) using the same resource.
- Assumption: Each UE knows its instantaneous CSI and the interference noise covariance matrix. BSs have access to the channel statistics.

Contributions:

- Identification of orthogonality conditions of optimal power allocation under the criterion of sum-rate maximization and the development of itertative algorithms for power allocation.
- Derive necessary conditions that characterize the power allocation matrices, which shows that the beams allocated to different users should be non-overlapping.
- Concave-convex and deterministic equivalence based power allocaton solutions for solving the sum-rate maximization problem.

Fast Unit-Modulus Least Squares With Applications in Beamforming

Goal:

- To solve ULS optimization problems.
- Applications: Phase only beamformer design for massive MIMO systems, radar code design, sensor network localization, phase retrieval etc.

Problem:

$$\min_{\mathbf{w}\in\mathbb{C}^N} \|\mathbf{y} - \mathbf{A}\mathbf{w}\|_2^2 \tag{1}$$

$$\text{subject to} \quad |w_i|^2 = 1, i = 1, \ldots, N.$$

Contributions:

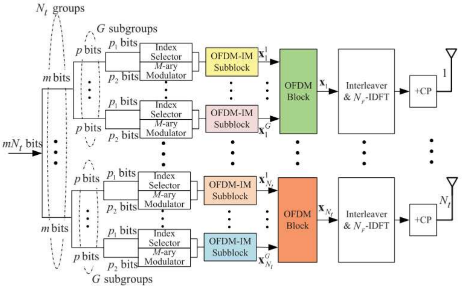
- Gradient projection to solve the ULS problem. Constraints are non convex, but the Lipschitz continuity of the gradient used to show the global convergence to a KKT point.
- Algorithms tailored for phase only array beamforming for massive MIMO systems. Alternating optimization algorithms that iterate between updating the antenna weights and the scale factors to get enhanced performance in terms of beam pattern accuracy. Global convergence shown.
- For transmit beamforming, an addition degree of freedom can be introduced. Alternating optimization algorithm proposed.

Multiple-Input Multiple-Output OFDM With Index Modulation: Low-Complexity Detector Design

Goal:

- Low complexity detector design for MIMO-OFDM-IM.

System Model:



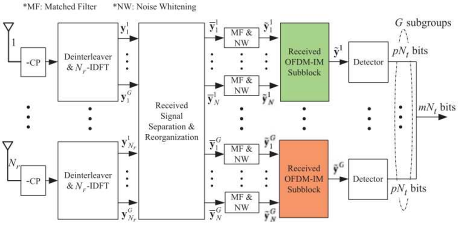


Fig. 2. Block diagram of MIMO-OFDM-IM receiver.

Multiple-Input Multiple-Output OFDM With Index Modulation: Low-Complexity Detector Design

Sequential Monte Carlo (SMC) Theory:

- Class of sampling based sequential Bayesian inference methodologies for general dynamic systems.
- MAP/ML needs exhaustive search. Objective of the SMC is to numerically approximate the aposteriori distributions, given some noisy and partial observations.
- Deterministic SMC: At each sampling interval, symbols are drawn from a given finite set to construct new sequential particles, and then update their corresponding importance weights. Based on the importance weights of all the hypotheses generated, only certain promising hypotheses are retained.

Contributions:

- Two types of detection algorithms based on the sequential Monte Carlo theory are proposed.
- (a) Deterministic SMC aided subblock-wise detection, and (b) deterministic SMC aided subcarrier-wise detection.
- QR decomposition applied to the channel matrix to get a lower triangular channel. SMC method applied by drawing samples from the first transmit antenna and ending to the last transmit antenna.
- For (a), each OFDM-IM subblock is considered as a super modulated symbol drawn from a large finite set, and then aposteriori distribution computed numerically. For (b), samples are drawn at the subcarrier level.

Superimposed Pilots Are Superior for Mitigating Pilot Contamination in Massive MIMO

Goal:

- Channel estimation based on superimposed pilots.
- Derivation of uplink SINR for the various schemes that are proposed.

System Model:

- TDD massive MIMO UL with L cells (BS with M antennas each) and K single antenna users per cell.
- Separate pilot and data phases or superimposed pilots.

$$\mathbf{Y}_j = \sum_{l=0}^{L-1} \sum_{k=0}^{K-1} \sqrt{\mu_{l,k}} \mathbf{h}_{j,l,k} \mathbf{s}_{l,k}^T + \mathbf{W}_j \tag{2}$$

Pilot Contamination:

- Pilot reuse in multiple cells results in the channel estimates of the desired users being contaminated with the channel vectors of users in adjacent cells, causing a loss in spectral efficiency.

Superimposed Pilots Are Superior for Mitigating Pilot Contamination in Massive MIMO

Superimposed Pilots:

$$\mathbf{Y}_j = \sum_{l=0}^{L-1} \sum_{k=0}^{K-1} \mathbf{h}_{j,l,k} \left(\rho_{l,k} \mathbf{x}_{l,k} + \lambda_{l,k} \mathbf{p}_{l,k} \right) + \mathbf{W}_j \tag{3}$$

Contributions:

- Proposed a non-iterative scheme for UL channel estimation based on superimposed pilots using LS and derived an expression for the UL SINR at the output of the matched filter.
- Power control and optimal choice of parameters λ and ρ needed but the problem is non-convex. Hence a suboptimal solution is provided and a lower bound on UL SINR derived.
- Proposed an iterative data aided channel estimation, where the estimated channel and data vectors of both the desired and interfering users are used to remove the interference term in the channel estimation error.
- Showed that a hybrid system is superior to an optimally designed system with only time multiplexed pilots. A simple implementation of the hybrid system is provided.

Stochastic Proximal Gradient Consensus Over Random Networks

Goal:

- To solve a structured version (smooth convex + non-smooth convex) of the global consensus problem.
- Applications in distributed and parallel machine learning and distributed signal processing.

Global consensus problem:

$$\min_y f(y) := \sum_{i=1}^{N} f_i(y). \tag{4}$$

- How to compute an optimal solution of (4), through a distributed process where each agent only utilizes local gradient information about its local objective.

Stochastic Proximal Gradient Consensus Over Random Networks contd.

Contributions:

- Structured version of the global consensus problem.

$$\min_{y} f(y) := \sum_{i=1}^{N} f_i(y) = \sum_{i=1}^{N} \left(g_i(y) + h_i(y)\right). \tag{5}$$

- Proposed an ADMM based method, named dynamic stochastic proximal-gradient consensus (DySPGC). Nodes are randomly activated (Stochasticity).
- Another algorithm proposed for static graphs called proximal gradient algorithm (PGC).
- Connections between the ADMM type methods and a few DSG-type methods.
- Showed that DySPGC generalizes other ADMM type methods such as the DLM and the IC-ADMM.
- Convergence Analysis of the proposed algorithms.

Other Interesting Papers

1. Source Association, DOA, and Fading Coefficients Estimation for Multipath Signals.
2. Magnetic MIMO Signal Processing and Optimization for Wireless Power Transfer.
3. Globally Optimal Energy-Efficient Power Control and Receiver Design in Wireless Networks.
4. Sub-Nyquist Cyclostationary Detection for Cognitive Radio.
5. Improved Cubature Kalman Filter for GNSS/INS Based on Transformation of Posterior Sigma-Points Error.
6. Poisson Multi-Bernoulli Mapping Using Gibbs Sampling.