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Outage Probability and Outage-Based Robust Beamforming for MIMO Interference Channels with Imperfect Channel State Information

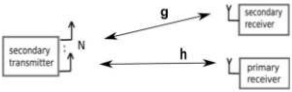
Juho Park, Youngchul Sung, Donggun Kim, and H. Vincent Poor
KAIST, South Korea and Princeton University

- Objective: Robust beam design in MIMO interference channels with imperfect CSI
- System model: K-user time-invariant MIMO interference channels with transmitter having N_t antennas and receiver N_r antennas
- Model the CSI error as circularly-symmetric complex Gaussian distributed
- Evaluate the closed form expression for outage probability (per user) for an arbitrarily given set of transmit and receive beamforming vectors
- Outage probability decreases exponentially w.r.t. the quality of CSI
- Iterative algorithm based on maximizing the weighted sum rate under per outage probability constraint

Performance Tradeoffs Offered by Beamforming in Cognitive Radio Systems: An Analytic Approach

Nadia Jamal and Patrick Mitran
University of Waterloo, Canada

- Model: Secondary transmitter with N antennas, Secondary receiver (SR) and Primary receiver (PR) with single antenna



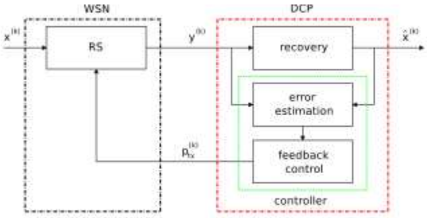
- Beamforming by Maximizing received power (G) at SR by constraining the interference power (I) to αP at PR
- Both perfect CSI and imperfect CSI cases are considered
- Derive closed form expressions for $\mathbb{E}[G]$ and $\mathbb{E}[I]$
- $\mathbb{E}[G]$ has a term independent of α and linearly dependent on N
- $\mathbb{E}[G]$ has another dominant term that increases as $\sqrt{\alpha}$ for small N (increase under imperfect CSI is less)
- $\mathbb{E}[I]$ is independent of N, thus concludes that null-steering beamforming can be employed

Sensing, Compression, and Recovery for WSNs: Sparse Signal Modeling and Monitoring Framework

Giorgio Quer, Riccardo Masiero, Gianluigi Pillonetto, Michele Rossi and Michele Zorzi
UCSD and University of Pagoda, Italy

- Nodes convey spatially and temporally correlated data to a data collection point (DCP)
- Employ principle component vectors as sparsifying basis
- PCA-Approximating an N-dim signal by an M-dim signal by projecting on to an M-dim subspace
- L sensors (randomly chosen) out of N sensors convey information
- Temporal correlation (K samples) is used at DCP to find the sparsifying basis (PCA basis) and then to reconstruct the M-sparse vector

WSN monitoring framework



- Random sampling
- Recovery using PC vectors as sparsifying basis
- Error Estimation and Feedback

A Frechet Mean Approach for Compressive Sensing Data Acquisition and Reconstruction in Wireless Sensor Networks

Wei Chen, Miguel R. D. Rodrigues and Ian J. Wassell
University of Cambridge and University College London

- This paper considers acquisition of data in WSNs
- Sparse Frechet Mean is used as the crude estimate of the sparse vector
- Least squares estimator can be used to obtain the sparse frechet mean
- Iterative algorithm: Penalised ℓ_1 minimization with penalty matrix determined by frechet mean
- Similarly, a matching pursuit algorithm is also proposed

Other papers

- Comments on “Spectrum Sensing in Cognitive Radio Using Goodness-of-Fit Testing”
- Joint Relay Selection and Power Allocation for Decode-and-Forward Cellular Relay Network with Channel Uncertainty
- An Efficient Maximum Likelihood Method for Direction-of-Arrival Estimation via Sparse Bayesian Learning
- Delay-optimal Power Control Policies