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New Iterative Detector of MIMO Transmission Using Sparse Decomposition

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Goal and Contributions

Goal : Iterative Decoding of MIMO signals using a sparse recovery framework.

Conventional Schemes:

- Maximum Likelihood Joint Detection (Huge complexity for MIMO)
- MMSE, ZF (High performance loss for underdetermined systems)
- Sphere Decoder (Achieves near optimal performance provided sphere search is well defined. Variable computational complexity)

Contributions :

- ML Detection problem modeled as a sparse signal recovery problem. Detecting the desired signal via quadratic minimization under convex constraints.
- Applying the proposed detector to a large scale antenna on nonselective channels and to MIMO systems on frequency selective channel.

System Model

Received signal in a MIMO single user channel is defined as

$$y = Hx + z$$
(1

$$y = HB_qs + z$$
(2)
Example: $Q = \{1, 3, 5\}$
 $q = [1, 3, 5]$
Dictionary
 $1 \to 1 \ 0 \ 0$
 $3 \to 0 \ 1 \ 0$
 $5 \to 0 \ 0 \ 1$
 x_1
 x_2
 x_3
 x_3

$$\mathbf{B}_{q} = \begin{pmatrix} \mathbf{q} & \mathbf{0}_{3} & \mathbf{0}_{3} \\ \mathbf{0}_{3} & \mathbf{q} & \mathbf{0}_{3} \\ \mathbf{0}_{3} & \mathbf{0}_{3} & \mathbf{q} \end{pmatrix}$$

Mathematical transformation

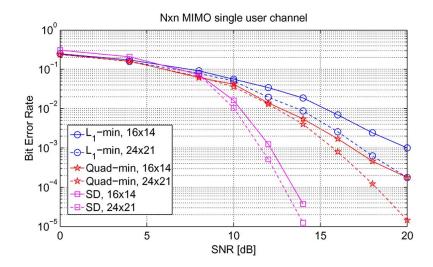
$$x_j = \mathbf{q} \cdot \mathbf{s}_j \longrightarrow \mathbf{x} = \mathbf{B}_q \cdot \mathbf{s},$$

 $\mathbf{1}_3^T \mathbf{s}_j = 1 \longrightarrow \mathbf{1}_3 = \mathbf{B}_1 \cdot \mathbf{s},$

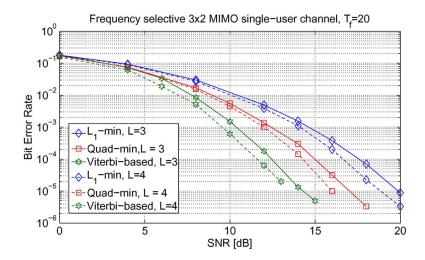
Solution: Quadratic programming model with linear equality constraints and nonnegative variables. $\arg\min_{s \in \mathbb{R}^{NM \times 1}} ||y - HB_q s||_2$

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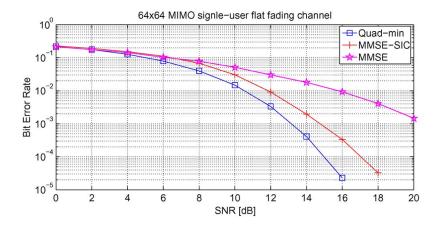
subject to $B_1s = 1_N$ and $s \ge 0$



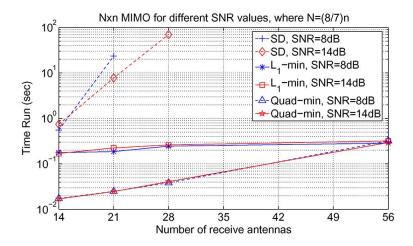
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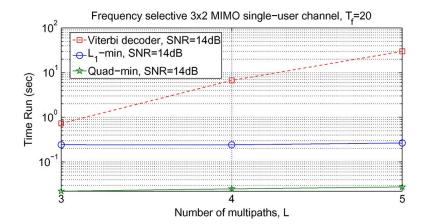
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Distributed Real-Time Implementation of Interference Alignment with Analog Feedback

Authors: Seogoo Lee, Andreas Gerstlauer and Robert W. Heath.

Goal and Contributions

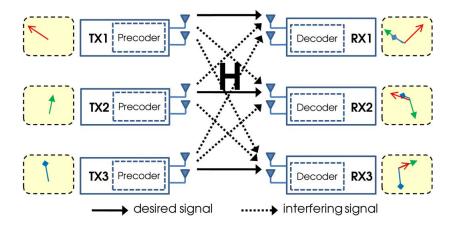
Goal : Investigation of real time IA performance on a fully distributed 2x2 MIMO prototype system with three physically independent user pairs.

Contributions

- Over the air algorithms for time and frequency synchronization, as well as analog feedback are studied and implemented.
- Sum rates are illustrated as a function of complexity and accuracy of different alignment, synchronization and feedback algorithms.

 Analog vs quantization based feedback approaches were evaluated.

Block Diagram of three-user 2x2 MIMO System



System Model

$$y_k = H_{k,k} F_k d_k + \sum_{m \neq k} H_{k,m} F_m d_m + n_k$$
(3)

where $H_{k,m}$ is the $N_r \times N_t$ channel matrix between the m^{th} transmitter and the k^{th} receiver

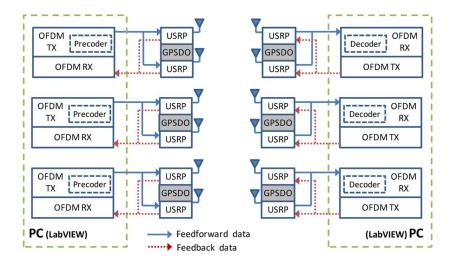
Interference Alignment: For IA with MIMO and a ZF combining matrix at the receivers, the received signal becomes

$$\hat{y}_{k} = W_{k}^{H}H_{k,k}F_{k}d_{k} + \sum_{m \neq k}W_{k}^{H}H_{k,m}F_{m}d_{m} + W_{k}^{H}n_{k} \qquad (4)$$

Sum Rate:

$$R_{sum} = \sum_{k=1}^{K} \log_2 \left| I_{N_s} + (\sigma_k^2 W_k^H W_k + R_k)^{-1} x (W_k^H H_{k,k} F_k F_k^H H_{k,k}^H W_k) \right|$$
(5)

Prototype Setup



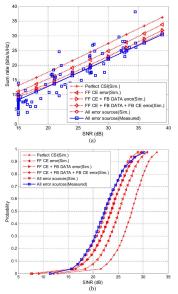
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Hardware and Software Setup

- NI's USRP-2921 hardware and LabVIEW software on two dual-core Intel Xeon 2.67GHz workstations
- USRPs of the transmitters work in transmitting mode for the training and data phases but in receiving mode for the feedback phase
- NI's LabVIEW for SDR implementation
- OFDM Parameters for the prototype:

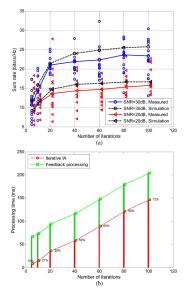
Fast Fourier transform (FFT) length	128
Cyclic prefix length	32
Number of null subcarriers	23
Number of data subcarriers (N_{sc})	105

Results: Sum Rate and Empirical CDF of the measured SINR



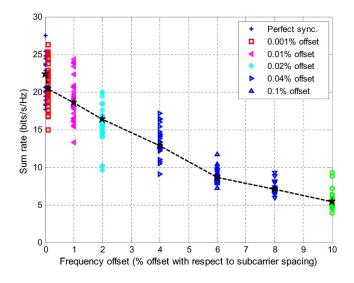
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Results: Complexity vs Performance Tradeoff of iterative IA method



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Results: IA Performance with the residual frequency synchronization error (SNR 30dB)



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	Perfect CSI	FF CE	FF CE+FB DATA	FF CE+FB DATA+FB CE	All error sources	Measures
Mean	27.45	24.9	23.4	23.4	22.4	22.5
Variance	9.3	11.1	12.5	13.3	13.2	15.4

Conclusion:

- Performance Study of IA in the presence of practical issues with an emphasis on the feedback quality
- Possible to implement IA in a distributed fashion while achieving predicted sum rate scaling
- Future work: To design a medium access control protocol that allows a fast setup of distributed IA clusters

Energy Conservation Routing in Multihop Wireless Networks

Authors: Weiwei Chen and Chin-Tau

Goal and Contributions

Goal : To design an energy conservation routing scheme in face of traffic uncertainty.

Contributions

- Proposal of a new energy conservation routing framework when traffic uncertainty is present.
- New approach immune from the two problems prevalent in conventional approaches: performance degradation caused by inaccuracy of a simplified interference model and instability caused by assumption of unbounded transmission power and data rate.
- Analytical and simulation results show that the proposed approach can achieve significant performance gains in terms of throughput and energy consumption.

System Model

System Model: STDMA-based wireless network (Time is divided into slots and slots form a frame)

- Traffic Demand Uncertainty model: Hose Model. Define the ingress and egress traffic of a node as the average amount of traffic entering to and exiting from this node.
- Let a_n and b_n be the given relative ingress and egress traffic intensities at node n. ζ denote the throughput scaling parameter
- Maximum allowable ingress and egress traffic at node n is

$$\sum_{f|src_f=n} h_f \le \zeta a_n \tag{6}$$

$$\sum_{f|dst_f=n} h_f \le \zeta b_n \tag{7}$$

System Model contd.

 Link Capacity Model: Received signal for link e can be expressed as

$$y_e(T, P_T) = \sum_{i|i \in T, i \neq v} \sqrt{g_{u,i}} x_i + \sqrt{g_{u,v}} x_v + n_0 \qquad (8)$$

where the first and the second terms correspond to the interference and the desired signal respectively $% \left({{{\left[{{{\left[{{\left[{{\left[{{\left[{{{\left[{{{\left[{{{\left[{{{\left[{{{\left[{{{\left[{{{\left[{{{\left[{{{}}} {{}}} \right]}}}} \right.}$

The SINR for link e is

$$\gamma_{e}(T, P_{T}) = \frac{P_{v}g_{u,v}}{\sum_{i|i\in T, i\neq v} P_{i}g_{u,i} + \kappa}$$
(9)

where κ is the power of the thermal noise at each transmitter.
The optimal modulation schemes (m_e(T, P_T)) and the correspoding transmission rate (c_e(T, P_T)) for link e are

$$k^* = \operatorname{argmax}_{\gamma_{e}}(T, P_{T}) \ge \gamma_{thr}^k$$
 (10)

$$m_e(T, P_T) = m_{k^*}(T, P_T), c_e(T, P_T) = o_{k^*}$$
 (11)

Energy Conservation Routing

Problem Formulation:

- Given [ζa_n, ζb_n], for any h_f that satisfy (4), find the routing that can maximize the network lifetime, which is defined to be the amount of time during which none of the nodes' batteries run out. ζ* is the maximum achievable throughtput of the network.
- Link Based Approach: Not considered in this paper.
- Node Based Approach: Set of nodes will be selected for transmission in a given slot. Performance is similar to link based approach if traffic matrix is given.

Energy Conservation Routing:

- \blacktriangleright Constrained optimization problem to maximize the network lifetime for a given throughput scaling parameter ζ
- \blacktriangleright τ_{ζ}^{*} be the maximum network lifetime for a given throughput scaling parameter ζ

$$\tau_{\zeta}^* = \max_{Y, U_{node}} \min_{H \in W_{\zeta}} \tau(H, Y, U_{node})$$
(12)

where H is the traffic demand matrix, Y is the routing scheme and U_{node} is the slot assignment scheme

 $\blacktriangleright \ \nu_{\zeta}^{*} = 1/\tau_{\zeta}^{*}$, ν_{ζ}^{*} can be derived from the optimization problem

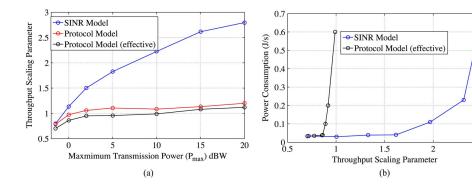
$$\min \nu_{\zeta}$$
 (13)

s.t

$$w_{v}(H, Y, U_{node}) \leq \nu_{\zeta} \phi_{v} y_{f,e}^{N}, \mu^{N}, \nu_{\zeta} \geq 0$$
(14)

One of the Results

(Problem solved using Colum generation method which decomposes the problem into a master and a subproblem. Section IIIC in paper)



 An Eigenvalue-Moment-Ratio Approach to Blind Spectrum Sensing for Cognitive Radio under Sample-starving environment

Authors: Lei Huang, Jun Fang, Kefei Liu, Hing Cheung So and Hongbin Li

Goal and Contributions

- EMR approach for spectrum sensing is proposed from RMT perspective and performs better than the state of the art algorithms
- Calculation of the theoretical decision threshold for the EMR method.
- Derivation of the asymptotic distribution of the EMR statistic in the presence of the signals.
- Reformulate the EMR detector in terms of the Frobenius inner product and matrix trace operations avoiding the eigen value decomposition (for computational complexity reduction).
- Simulation Results are presented to illustrate the superiority of the EMR approach and confirm the theoretical calculation.

Problem Formulation

- Signal Model: MIMO CR network where the SU has m antennas to receive the signals emitted by d (d < m) PUs with a single antenna
- ► The output of the SU, x_k(k = 1, ..., n), under two hypothesis H0 and H1 can be written as

$$x_k = w_k, H0 \tag{15}$$

$$x_k = Hs_k + w_k, H1 \tag{16}$$

where x_k, s_k, w_k stand for the observation, signal and noise vectors at the kth sampling instant respectively

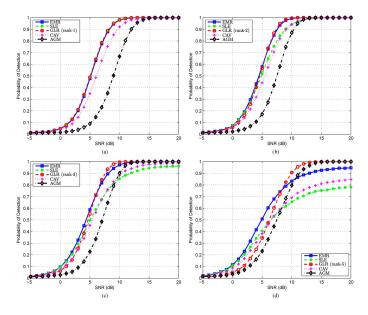
Conventional Spectrum Sensing Techniques:

- Full PU signal characteristics, CSI available at the CR receiver
 - Cyclostationary detection
 - Matched Filtering
 - Energy detection
- Blind Spectrum Sensing Methodologies
 - Covariance Absolute Value (CAV) Detector
 - Generalized Likelihood ratio (GLR) test (Arithmetic to geometric mean (AGM) algorithm)

EMR Detector

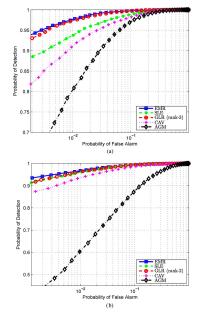
- Derivation of blind EMR algorithm from RMT perspective
- Analyze the performance in terms of detection probability P_d and false alarm probability P_{fa}
- Theoretical threshold for EMR approach is determined.
- Asymptotic distribution of ξ_{EMR} under H1 based on the RMT and then use it to obtain an approximate analytical formula for the detection probability.

Simulation Results



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Simulation Results



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Conclusion:

- EMR algorithm devised to handle the blind spectrum sensing in sample starving environments.
- As the EMR detector is derived from the RMT perspective and utilizes all the signal eigenvalues for detection, it outperforms other blind detectors particularly for relatively small sample scenarios.

Other interesting papers

Robust Stochastic Optimization for MISO Broadcast Channel with Delayed CSIT and Limited Transmitting Antennas

Authors : Y.Luo and T.Ratnarajah

 Robust Multiuser Sequential Channel Sensing and Access in Dynamic Cognitive Radio Networks: Potential Games and Stochastic Learning Authors : Y. Xu, Q.Wu, J.Wang, L.Shen and A.Anpalagan

 Quality-Optimized Joint Source Selection and Power Control for Wireless Multimedia D2D Communication Using Stackelberg Game

Authors: Q.Wang, W.Wang, S.Jin, H.Zhu and N.T.Zhang