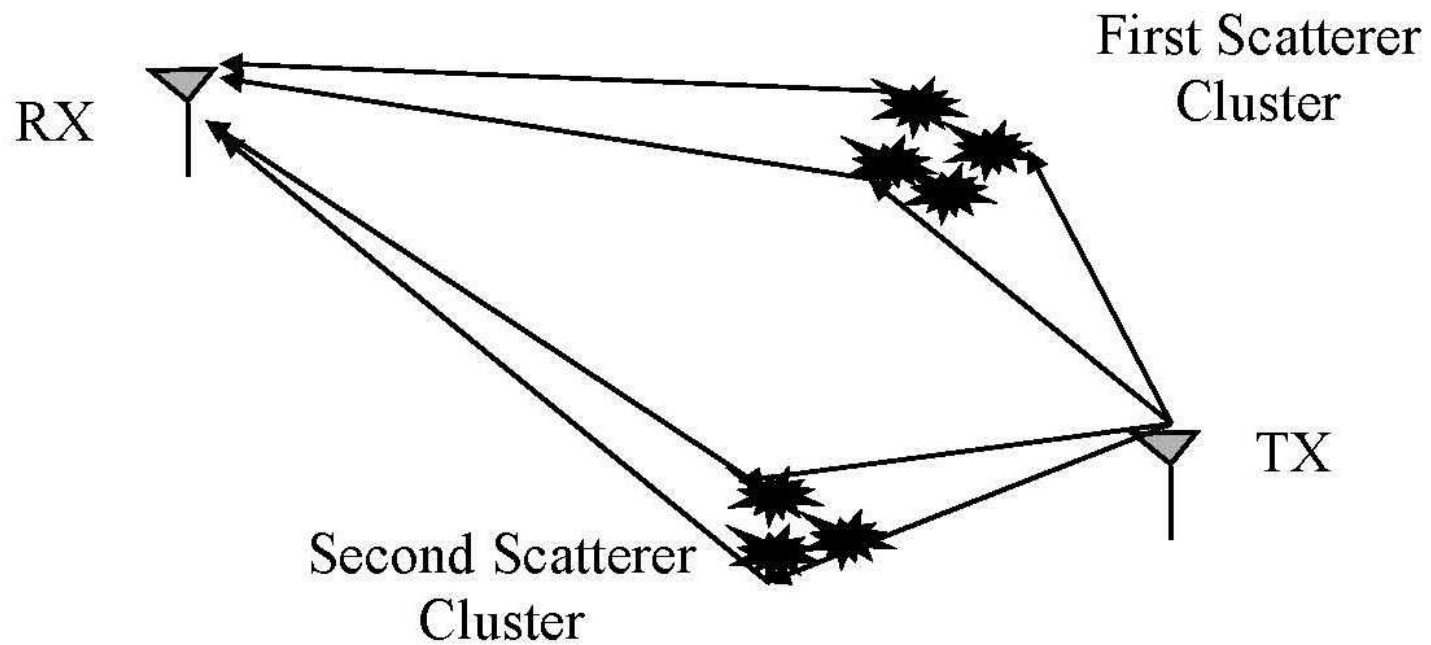


# An Optimal Transmitting Scheme for MIMO-OFDM Systems with Spatial Correlation Feedback

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- Introduction
- Motivation
- System model
- Performance analysis
- Nonlinear programming concepts
- Numerical solution
- Conclusions and future work



Different Scatterers are independent.

- Degrees of Channel State Information at the transmitter:
  - Perfect CSI (unpractical )
  - Mean Feedback (applications with low mobility)
  - Covariance Feedback (applications that involve mobile transmitters and/or receivers)
- The channel model that is widely used: Flat Fading Scenario which models narrowband applications (Speech)
- Frequency Selective Fading: Models broadband applications (high data rate, multimedia applications , and others) Only Perfect CSI: (Cioffi et. al., SP 03) and Mean Feedback: (Giannakis et. al., SP 04)

- MIMO-OFDM frequency selective fading channel model with  $M_t$  transmit antennas and  $M_r$  receive antennas.
- The channel impulse response from transmit antenna  $i$  to receive antenna  $j$  at any time instant  $\tau$  can be modeled as

$$h_{ij}(\tau) = \sum_{l=0}^{L-1} \alpha_{ij}(l) \delta(\tau - \tau_l), \quad (1)$$

- The received signal at the  $n$ -th subcarrier at receive antenna  $j$  is given by

$$y_j(n) = \sqrt{\frac{\rho}{M_t}} \mathbf{h}_j^T(n) \mathbf{b}(n) + v_j(n), \quad (2)$$

- In general, the design of the SF-beamformer symbol  $\mathbf{B}$  is split into two parts  $\mathbf{B} = \mathbf{W}\mathbf{C}$ .
- A predesigned SF codeword  $\mathbf{C}$
- A beamformer (linear transformation)  $\mathbf{W}$  which is an  $M_t \times M_t$  matrix
- We seek the beamformer design  $\mathbf{W}$  !!!

- Objective: Minimize the average pairwise error probability

$$Pr(\mathbf{B} \rightarrow \tilde{\mathbf{B}}) \quad (3)$$

- We can prove that the average pairwise error probability can be upper bounded by

$$PEP \leq \left[ \det \left( \frac{\rho}{4M_t} \tilde{\mathbf{R}}^H \left( I_{NM_r} \otimes \left[ (I_N \otimes \mathbf{W}) \Delta (I_N \otimes \mathbf{W}^H) \right] \right) \tilde{\mathbf{R}} + I_r \right) \right]^{-1} \quad (4)$$

- Where  $\tilde{\mathbf{R}}$  is the square root matrix of the channel correlation matrix  $\mathbf{R}_h = E \{ \mathbf{h} \mathbf{h}^H \}$

$$\mathbf{R}_h = \tilde{\mathbf{R}} \tilde{\mathbf{R}}^H \quad (5)$$

- We can state the optimization problem as follows

$$\begin{aligned} \max_{\mathbf{W}} f(\mathbf{W}) &= \det \left( \frac{\rho}{4M_t} \tilde{\mathbf{R}}^H \left( I_{NM_r} \otimes \left[ (I_N \otimes \mathbf{W}) \Delta (I_N \otimes \mathbf{W}^H) \right] \right) \tilde{\mathbf{R}} \right. \\ &\quad \left. + I_r \right) \\ \text{s.t. } \|\mathbf{W}\|_F^2 &= 1. \end{aligned} \tag{6}$$

- Is it convex? (Hopefully!)
- $\Delta$  is a positive semi-definite Hermitian matrix that depends on the SF code design
- Relaxation: Assume the matrix  $\Delta$  to be identity!



- The optimization problem then reduces to

$$\begin{aligned} \max_{\mathbf{W}} f(\mathbf{W}) &= \det \left( \frac{\rho}{4M_t} \tilde{\mathbf{R}}^H \left( I_{NM_r} \otimes \left[ (I_N \otimes \mathbf{W}) (I_N \otimes \mathbf{W}^H) \right] \right) \tilde{\mathbf{R}} + I_r \right) \\ \text{s.t. } \|\mathbf{W}\|_F^2 &= 1. \end{aligned} \tag{7}$$

- Define  $\eta = \mathbf{W}\mathbf{W}^H$ .

Matrix identity  $(I_N \otimes A)(I_N \otimes A^H) = I_N \otimes (AA^H)$

- The optimization problem can be rewritten as follows

$$\begin{aligned} \max_{\eta} g(\eta) &= \det \left( \frac{\rho}{4M_t} \tilde{\mathbf{R}}^H \left( I_{NM_r} \otimes (I_N \otimes \eta) \right) \tilde{\mathbf{R}} + I_r \right) \\ \text{s.t. } \text{tr}(\eta) &= 1, \\ \eta &= \eta^H \geq 0. \end{aligned} \tag{8}$$

- Using the matrix identity  $I_N \otimes (I_M \otimes A) = I_{NM} \otimes A$

- The objective function can be finally written as

$$\begin{aligned} \max_{\eta} g(\eta) &= \det \left( \frac{\rho}{4M_t} \tilde{\mathbf{R}}^H (I_{N^2 M_r} \otimes \eta) \tilde{\mathbf{R}} + I_r \right) \\ \text{s.t. } \text{tr}(\eta) &= 1, \\ \eta &= \eta^H \geq 0. \end{aligned} \tag{9}$$

- First we study the convexity of the feasible region

Let  $\eta = \lambda\eta_1 + (1 - \lambda)\eta_2$ , where  $\lambda \in (0, 1)$

- Then we have

$$\begin{aligned} \text{tr}(\eta) &= \text{tr}(\lambda\eta_1 + (1 - \lambda)\eta_2) = \lambda\text{tr}(\eta_1) + (1 - \lambda)\text{tr}(\eta_2) \\ &= \lambda + (1 - \lambda) = 1. \end{aligned}$$

(10)

- Substituting  $\eta = \lambda\eta_1 + (1 - \lambda)\eta_2$  in  $g(\eta)$

$$\begin{aligned}
 g(\eta) &= \det \left( \frac{\rho}{4M_t} \tilde{\mathbf{R}}^H \left( I_{N^2M_r} \otimes (\lambda\eta_1 + (1 - \lambda)\eta_2) \right) \right. \\
 &\quad \left. \times \tilde{\mathbf{R}} + I_r \right) \\
 &= \det \left( \lambda \frac{\rho}{4M_t} \tilde{\mathbf{R}}^H \left( I_{N^2M_r} \otimes \eta_1 \right) \tilde{\mathbf{R}} + (1 - \lambda) \frac{\rho}{4M_t} \tilde{\mathbf{R}}^H \left( I_{N^2M_r} \otimes \eta_2 \right) \right)
 \end{aligned} \tag{11}$$

- **Corollary (Matrix Analysis)** For any positive definite matrices  $A$  and  $B$  and  $\lambda \in (0, 1)$ , the following is true

$$\det [\lambda A + (1 - \lambda)B] \geq \det [A]^\lambda \det [B]^{1-\lambda}. \tag{12}$$

- Using this corollary, we get

$$g(\eta) \geq g(\eta_1)^\lambda g(\eta_2)^{1-\lambda}. \tag{13}$$

- Define  $q(\eta) = \log(g(\eta))$ , then the above equation reduces to

$$q(\eta) \geq \lambda q(\eta_1) + (1 - \lambda)q(\eta_2). \quad (14)$$

- Therefore  $q(\eta)$  is a concave function!
- Now we can write the optimization problem again as follows

$$\begin{aligned} \max_{\eta} q(\eta) &= \log \left( \det \left( \frac{\rho}{4M_t} \tilde{\mathbf{R}}^H \left( I_{N^2 M_r} \otimes \eta \right) \tilde{\mathbf{R}} + I_r \right) \right) \\ \text{s.t. } \text{tr}(\eta) &= 1, \\ \eta &= \eta^H \geq 0. \end{aligned} \quad (15)$$

- This is maximizing a concave function over a convex set  
Local optima are global optima !

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- To solve the optimization problem we choose the sequential quadratic programming (SQP) method.
  - Consider solving the following problem

$$\begin{aligned} \min_x f(x) \\ g_i(x) = 0, \quad 1 \leq i \leq m_e \\ g_i(x) \leq 0, \quad m_e + 1 \leq i \leq m, \\ x \in \mathcal{R}^n. \end{aligned} \tag{16}$$

- For a given iteration  $k$ , let  $x_k$  be an approximation to the solution,  $\lambda_k$  be an approximation to the multipliers, and  $B_k$  an approximation to the Hessian matrix of the Lagrangian

- we have to solve the following quadratic programming problem

$$\begin{aligned}
 & \min_d \frac{1}{2} d^T B_k d + \nabla f(x_k)^T d \\
 & \text{s.t. } \nabla g_i(x_k)^t d + g_i(x_k) = 0, \quad 1 \leq i \leq m_e, \\
 & \quad \nabla g_i(x_k)^t d + g_i(x_k) \leq 0, \quad m_e + 1 \leq i \leq m,
 \end{aligned} \tag{17}$$

- Let  $d_k$  be the optimal solution of the above subproblem and  $\mu_k$  the corresponding multipliers, then the next iteration is formulated as follows

$$\begin{pmatrix} x_{k+1} \\ \lambda_{k+1} \end{pmatrix} = \begin{pmatrix} x_k \\ \lambda_k \end{pmatrix} + \alpha_k \begin{pmatrix} d_k \\ \mu_k - \lambda_k \end{pmatrix} \tag{18}$$

- SQP is implemented in the Matlab optimization toolbox by the function 'fmincon'

- In the simulation experiments, the square root of the channel covariance matrix was taken to be

$$\tilde{\mathbf{R}}^H = \begin{bmatrix} -0.6918 & 1.2540 & -1.4410 & -0.3999 & 0.8156 & 1.2902 & 1.0000 \\ -1.5937 & 0.5711 & 0.6900 & 0.7119 & 0.6686 & -1.2025 & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \end{bmatrix} \quad (19)$$

- The matrix  $\eta$  is a  $2 \times 2$  symmetric matrix, i.e. 3 unknowns.
- The cost function can be simplified as follows

$$q(\eta) = \log(13.57 * \eta(1, 1)^2 - 5.8645 * \eta(1, 2)^2 + 9.88 * \eta(2, 2)^2 - \eta(1, 1) * \eta(2, 2) + 28 * \eta(1, 1) * \eta(2, 1) + 10.75 * \eta(1, 2) * \eta(2, 1) + (4/SNR) * (\eta(1, 1) * \eta(2, 1) + 0.8572 * \eta(1, 2) + 6.88 * \eta(2, 1) + 1)). \quad (20)$$

- We tested the algorithm at more than initial point and they all gave the same result as follows

$$\begin{aligned}x_o &= [0.5, 0, 0.5]; \\x_o &= [1, 0, 0]; \\x_o &= [0, 0, 1], \\x_o &= [0.2, 0, 0].\end{aligned}\tag{21}$$

The optimal solution at any of the above initial conditions was

$$\eta_1(1, 1) = 0.3416, \quad \eta_1(1, 2) = 0.4742, \quad \eta_1(2, 2) = 0.6584.\tag{22}$$

- The above answer was at  $SNR = 100$ . We changed the  $SNR$  to check the sensitivity of the optimal solution to changing the  $SNR$ .



- We considered  $SNR = 10$  and the results were

$$\eta_2(1, 1) = 0.3614, \quad \eta_2(1, 2) = 0.4804, \quad \eta_2(2, 2) = 0.6386. \quad (23)$$

- Thus the optimal solution is not sensitive to the variations in the SNR.
- Although this phenomenon was only checked for this specific example, it is intuitive to generalize it.

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- We studied the problem of optimal transmitter design in the presence of partial channel state information
  - We formulated the problem as a non-linear optimization problem where the objective function is an upper-bound on the system pairwise error probability and the constraints are on the system energy
  - Under a relaxation on the objective function, we prove that the optimization problem is convex
  - We utilize the sequential quadratic programming methods to solve the problem
  - Future Work