



Robust Artificial-Noise Aided Transmit Design for Multi-User MISO Systems with Integrated Services

Weidong Mei, Zhi Chen, and Chuan Huang

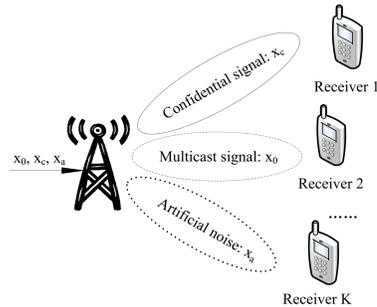
National Key Laboratory of Science and Technology on Communications, No.2006, Xiyuan Ave, Chengdu, China

Background

- Physical-layer (PHY) security and multicasting
 - PHY security can overcome the inherent difficulties of cryptographic methods.
 - PHY-multicasting transmits common messages in a way that all receivers can decode them.
 - Traditionally they are independently investigated.
- PHY service integration
 - merging multiple services into one integral service for one-time transmission.
 - enable coexisting services to share the same resources, thereby significantly increasing the spectral efficiency.
- Motivation
 - Many works focused on PHY service integration only from the viewpoint of information theory.
 - ✓ DMBC (Csiszar et al. '78)
 - ✓ MIMO (Ly et al. '10)
 - ✓ Bidirectional relay (Wyrembelski et al. '12)
 - ✓ Compound BC with uncertainties (Wyrembelski et al. '12)
 - How to derive certain transmit design to achieve the boundary points of the secrecy rate region?

System Model

- A multi-antenna transmitter serves K receivers, and each receiver has a single antenna.
- All receivers have ordered the multicast service and receiver 1 further ordered the confidential service.



- The received signal at receiver k

$$y_k = \mathbf{h}_k \mathbf{x} + z_k$$

\mathbf{h}_k -kth receiver's channel response z_k -AWGN
- Transmitted components

$$\mathbf{x} = \mathbf{x}_0 + \mathbf{x}_c + \mathbf{x}_a$$

\mathbf{x}_0 -multicast message, $\mathbf{x}_0 \sim CN(\mathbf{0}, \mathbf{Q}_0)$
 \mathbf{x}_c -confidential message, $\mathbf{x}_c \sim CN(\mathbf{0}, \mathbf{Q}_c)$
 \mathbf{x}_a -artificial noise, $\mathbf{x}_a \sim CN(\mathbf{0}, \mathbf{Q}_a)$
- Deterministically bounded CSI error model

$$\mathbf{h}_k = \tilde{\mathbf{h}}_k + \mathbf{e}_k, \|\mathbf{e}_k\|_F^2 \leq \varepsilon_k^2$$

Robust Scheme

- Worst-case secrecy rate region
Under the above described deterministically bounded CSI error model, an achievable worst-case secrecy rate region is determined by [Ly et al. '10]

$$R_c \leq \min_{k \in \mathcal{K}_c} \log \frac{\min_{\mathbf{h}_1 \in B_1} 1 + (\mathbf{h}_1 \mathbf{Q}_a \mathbf{h}_1^H)^{-1} \mathbf{h}_1 \mathbf{Q}_c \mathbf{h}_1^H}{\max_{\mathbf{h}_k \in B_k} 1 + (\mathbf{h}_k \mathbf{Q}_a \mathbf{h}_k^H)^{-1} \mathbf{h}_k \mathbf{Q}_c \mathbf{h}_k^H}$$

$$R_0 \leq \min_{\substack{k \in \mathcal{K} \\ \mathbf{h}_k \in B_k}} \log \left(1 + \frac{\mathbf{h}_k \mathbf{Q}_0 \mathbf{h}_k^H}{1 + \mathbf{h}_k (\mathbf{Q}_c + \mathbf{Q}_a) \mathbf{h}_k^H} \right)$$

where $B_k = \{\mathbf{h}_k | \mathbf{h}_k = \tilde{\mathbf{h}}_k + \mathbf{e}_k\}$, $\mathcal{K} = \{1, 2, \dots, K\}$, $\mathcal{K}_c = \mathcal{K} \setminus \{1\}$

Problem Formulation

$$g^*(\tau) = \max_{\mathbf{Q}_0, \mathbf{Q}_a, \mathbf{Q}_c} \log \frac{\min_{\mathbf{h}_1 \in B_1} 1 + (\mathbf{h}_1 \mathbf{Q}_a \mathbf{h}_1^H)^{-1} \mathbf{h}_1 \mathbf{Q}_c \mathbf{h}_1^H}{\max_{\substack{k \in \mathcal{K}_c \\ \mathbf{h}_k \in B_k} 1 + (\mathbf{h}_k \mathbf{Q}_a \mathbf{h}_k^H)^{-1} \mathbf{h}_k \mathbf{Q}_c \mathbf{h}_k^H}$$

$$s.t. \quad \min_{\substack{k \in \mathcal{K} \\ \mathbf{h}_k \in B_k}} \left\{ \log \frac{1 + \mathbf{h}_k (\mathbf{Q}_c + \mathbf{Q}_a + \mathbf{Q}_0) \mathbf{h}_k^H}{1 + \mathbf{h}_k (\mathbf{Q}_c + \mathbf{Q}_a) \mathbf{h}_k^H} \right\} \geq \tau, \quad (1)$$

$$\text{Tr}(\mathbf{Q}_0 + \mathbf{Q}_a + \mathbf{Q}_c) \leq P, \quad \text{Demand for QoS}$$

$$\mathbf{Q}_0 \succeq \mathbf{0}, \mathbf{Q}_a \succeq \mathbf{0}, \mathbf{Q}_c \succeq \mathbf{0},$$

This optimization problem also provides us a way to determine the boundary points of the secrecy rate region, by traversing all possible τ 's.

Further simplify (1) by introducing a slack variable β

$$g^*(\tau) = \max_{\mathbf{Q}_0, \mathbf{Q}_a, \mathbf{Q}_c, \beta} \min_{\mathbf{h}_1 \in B_1} \log \left(\frac{1 + \mathbf{h}_1 (\mathbf{Q}_c + \mathbf{Q}_a) \mathbf{h}_1^H}{\beta (1 + \mathbf{h}_1 \mathbf{Q}_a \mathbf{h}_1^H)} \right)$$

$$s.t. \quad (\beta - 1)(1 + \mathbf{h}_k \mathbf{Q}_a \mathbf{h}_k^H) - \mathbf{h}_k \mathbf{Q}_c \mathbf{h}_k^H \geq 0, \forall \mathbf{h}_k \in B_k, k \in \mathcal{K}_c, \quad (2)$$

$$\mathbf{h}_k \mathbf{Q}_0 \mathbf{h}_k^H - \tau' \mathbf{h}_k \mathbf{Q}_a \mathbf{h}_k^H - \tau' \mathbf{h}_k \mathbf{Q}_c \mathbf{h}_k^H - \tau' \geq 0, \forall \mathbf{h}_k \in B_k, k \in \mathcal{K},$$

$$\text{Tr}(\mathbf{Q}_0 + \mathbf{Q}_a + \mathbf{Q}_c) \leq P,$$

$$\mathbf{Q}_0 \succeq \mathbf{0}, \mathbf{Q}_a \succeq \mathbf{0}, \mathbf{Q}_c \succeq \mathbf{0}, \quad \tau' \triangleq 2^{\tau} - 1$$

Since this problem is non-convex and challenging to solve directly. To deal with it, we recast it into a two-stage optimization problem.

Problem Re-Formulation

The outer-stage part is with regard to (w.r.t.) β

$$\gamma^*(\tau') = \max_{\beta} \eta(\tau', \beta)$$

$$s.t. \quad 1 \leq \beta \leq 1 + P \min_{\mathbf{h}_1 \in B_1} \|\mathbf{h}_1\|^2$$

where $\log \gamma^*(\tau') = g^*(\tau')$. The inner-stage part calculates $\eta(\tau', \beta)$ for a fixed β

$$\eta(\tau', \beta) = \max_{\mathbf{Q}_0, \mathbf{Q}_a, \mathbf{Q}_c} \min_{\mathbf{h}_1 \in B_1} \frac{1 + \mathbf{h}_1 (\mathbf{Q}_c + \mathbf{Q}_a) \mathbf{h}_1^H}{\beta (1 + \mathbf{h}_1 \mathbf{Q}_a \mathbf{h}_1^H)}$$

$$s.t. \quad (\beta - 1)(1 + \mathbf{h}_k \mathbf{Q}_a \mathbf{h}_k^H) - \mathbf{h}_k \mathbf{Q}_c \mathbf{h}_k^H \geq 0, \forall \mathbf{h}_k \in B_k, k \in \mathcal{K}_c, \quad (3)$$

$$\mathbf{h}_k \mathbf{Q}_0 \mathbf{h}_k^H - \tau' \mathbf{h}_k \mathbf{Q}_a \mathbf{h}_k^H - \tau' \mathbf{h}_k \mathbf{Q}_c \mathbf{h}_k^H - \tau' \geq 0, \forall \mathbf{h}_k \in B_k, k \in \mathcal{K},$$

$$\text{Tr}(\mathbf{Q}_0 + \mathbf{Q}_a + \mathbf{Q}_c) \leq P,$$

$$\mathbf{Q}_0 \succeq \mathbf{0}, \mathbf{Q}_a \succeq \mathbf{0}, \mathbf{Q}_c \succeq \mathbf{0}.$$

□ The inner-stage optimization

➤ By resorting to the *S-procedure* [1], we can recast the above optimization as follows

$$\begin{aligned} \eta(\tau', \beta) = & \max_{\substack{\mathbf{Q}_0, \mathbf{Q}_a, \mathbf{Q}_c \\ \{t_k\}_{k \in \mathcal{C}}, \{\delta_k\}_{k \in \mathcal{C}}}} \min_{\mathbf{h}_1 \in \mathcal{B}_1} \frac{1 + \mathbf{h}_1(\mathbf{Q}_c + \mathbf{Q}_a)\mathbf{h}_1^H}{\beta(1 + \mathbf{h}_1\mathbf{Q}_a\mathbf{h}_1^H)} \\ \text{s.t. } & \mathbf{T}_k(\beta, \mathbf{Q}_c, \mathbf{Q}_a, t_k) \succeq \mathbf{0}, t_k \geq 0, \forall k \in \mathcal{C}, \\ & \mathbf{S}_k(\tau', \mathbf{Q}_c, \mathbf{Q}_a, \mathbf{Q}_0, \delta_k) \succeq \mathbf{0}, \delta_k \geq 0, \forall k \in \mathcal{C}, \\ & \text{Tr}(\mathbf{Q}_0 + \mathbf{Q}_a + \mathbf{Q}_c) \leq P, \\ & \mathbf{Q}_0 \succeq \mathbf{0}, \mathbf{Q}_a \succeq \mathbf{0}, \mathbf{Q}_c \succeq \mathbf{0}. \end{aligned} \quad (4)$$

where

$$\mathbf{T}_k(\beta, \mathbf{Q}_c, \mathbf{Q}_a, t_k) = \begin{bmatrix} t_k \mathbf{I} + (\beta - 1)\mathbf{Q}_a - \mathbf{Q}_c & ((\beta - 1)\mathbf{Q}_a - \mathbf{Q}_c)\tilde{\mathbf{h}}_k^H \\ \tilde{\mathbf{h}}_k((\beta - 1)\mathbf{Q}_a - \mathbf{Q}_c) & \tilde{\mathbf{h}}_k((\beta - 1)\mathbf{Q}_a - \mathbf{Q}_c)\tilde{\mathbf{h}}_k^H - t_k \varepsilon_k^2 + \beta - 1 \end{bmatrix}$$

$$\mathbf{S}_k(\tau', \mathbf{Q}_c, \mathbf{Q}_a, \mathbf{Q}_0, \delta_k) = \begin{bmatrix} \delta_k \mathbf{I} + \mathbf{Q}_0 - \tau'(\mathbf{Q}_a + \mathbf{Q}_c) & (\mathbf{Q}_0 - \tau'(\mathbf{Q}_a + \mathbf{Q}_c))\tilde{\mathbf{h}}_k^H \\ \tilde{\mathbf{h}}_k(\mathbf{Q}_0 - \tau'(\mathbf{Q}_a + \mathbf{Q}_c)) & -\delta_k \varepsilon_k^2 - \tau' + \tilde{\mathbf{h}}_k(\mathbf{Q}_0 - \tau'(\mathbf{Q}_a + \mathbf{Q}_c))\tilde{\mathbf{h}}_k^H \end{bmatrix}$$

– *S-procedure*

Let $\varphi_k(\mathbf{x}) = \mathbf{x}^H \mathbf{A}_k \mathbf{x} + 2\Re\{\mathbf{b}_k^H \mathbf{x}\} + c_k$, where $\mathbf{A}_k \in \mathbb{H}^n$, $\mathbf{b}_k \in \mathbb{C}^n$, $c_k \in \mathbb{R}$. The implication $\varphi_1(\mathbf{x}) \leq 0 \Rightarrow \varphi_2(\mathbf{x}) \leq 0$ holds if and only if there exists a $\mu \geq 0$ such that

$$\mu \begin{bmatrix} \mathbf{A}_1 & \mathbf{b}_1 \\ \mathbf{b}_1^H & c_1 \end{bmatrix} - \begin{bmatrix} \mathbf{A}_2 & \mathbf{b}_2 \\ \mathbf{b}_2^H & c_2 \end{bmatrix} \succeq \mathbf{0}$$

The remaining difficulty in solving (4) lies in its objective function, especially the uncertainty therein.

[1] S. Boyd and L. Vandenberghe, Convex optimization. Cambridge university press, 2009..

➤ Identification of the quasi-concavity of (4)

Property 1: Let us define

$$f(\mathbf{Q}_c, \mathbf{Q}_a) = \min_{\mathbf{h}_1 \in \mathcal{B}_1} \frac{1 + \mathbf{h}_1(\mathbf{Q}_c + \mathbf{Q}_a)\mathbf{h}_1^H}{\beta(1 + \mathbf{h}_1\mathbf{Q}_a\mathbf{h}_1^H)}$$

Then $f(\mathbf{Q}_c, \mathbf{Q}_a)$ is a quasi-concave function on the problem domain of (4), and hence the maximization problem (4) is a quasi-concave problem.

Proof: We just need to verify the convexity of the α -superlevel set of $f(\mathbf{Q}_c, \mathbf{Q}_a)$.

$$S_\alpha = \{f(\mathbf{Q}_c, \mathbf{Q}_a) | \mathbf{Q}_a \succeq \mathbf{0}, \mathbf{Q}_c \succeq \mathbf{0}, f(\mathbf{Q}_c, \mathbf{Q}_a) \geq \alpha\}$$

By using the *S-procedure* again, one can easily obtain

$$f(\mathbf{Q}_c, \mathbf{Q}_a) \geq \alpha \Leftrightarrow \mathbf{X}(\beta, \mathbf{Q}_c, \mathbf{Q}_a, \rho) \succeq \mathbf{0}$$

where

$$\mathbf{X}(\beta, \mathbf{Q}_c, \mathbf{Q}_a, \rho) = \begin{bmatrix} \rho \mathbf{I} + (1 - \alpha\beta)\mathbf{Q}_a + \mathbf{Q}_c & ((1 - \alpha\beta)\mathbf{Q}_a + \mathbf{Q}_c)\tilde{\mathbf{h}}_k^H \\ \tilde{\mathbf{h}}_k((1 - \alpha\beta)\mathbf{Q}_a + \mathbf{Q}_c) & \tilde{\mathbf{h}}_k((1 - \alpha\beta)\mathbf{Q}_a + \mathbf{Q}_c)\tilde{\mathbf{h}}_k^H - \rho \varepsilon_k^2 - \alpha\beta + 1 \end{bmatrix}$$

The proof is completed. ■

Consequently, the optimization problem (4) can be efficiently solved by combining a bisection search [1] with a convex optimization solver, e.g., CVX.

Numerical Results

➤ $N_f=2, K=5$

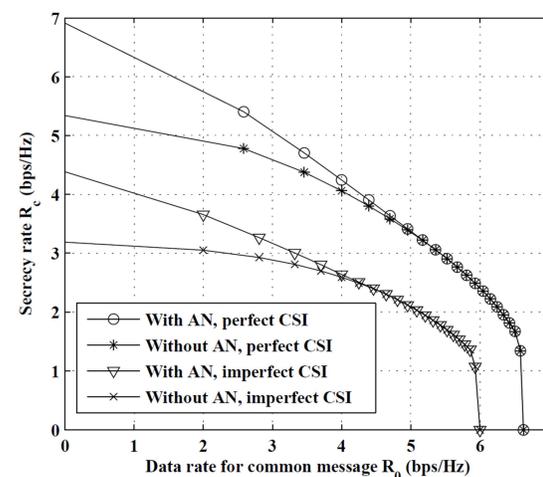
➤ Channel responses

$$\tilde{\mathbf{h}}_1 = [2, 0.4], \tilde{\mathbf{h}}_k = [0.9 - 0.1k, 0.5 + 0.1k], k \in \mathcal{C}_e$$

➤ $P=20\text{dB}$

➤ $\varepsilon_k=0.2$ for all k

□ Worst-case secrecy rate regions

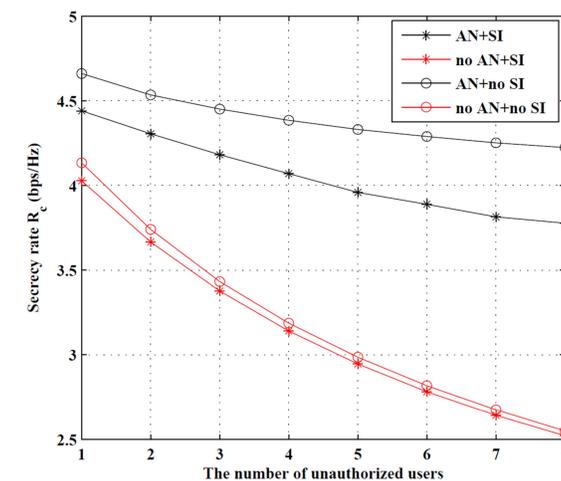


➤ The existence of channel uncertainty dramatically diminishes the achievable secrecy rate region

➤ AN indeed enhances the security performance without compromising the QoMS.

➤ The gap tends to be reduced, which implies that AN is prohibitive at high QoMS region.

□ Secrecy rate versus #unauthorized receivers



➤ The worst secrecy rates drops with the number of unauthorized receivers.

➤ Incorporating service integration restrains the maximum worst-case secrecy rates

Concluding Remarks

□ Considered the optimal robust AN-aided transmit design for multiuser MISO broadcast channel with confidential service and multicast service.

□ By resorting to a two-stage reformulation, the problem can be handled by solving a sequence of fractional SDPs.

□ AN can effectively fortify the transmission security, but high demand for QoMS will confine its use in turn.