

MIMO Optical Communication in Free Space

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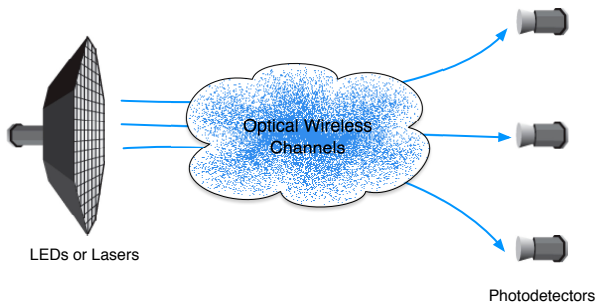
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joint work with Longguang Li, Stefan Moser, and Ligong Wang

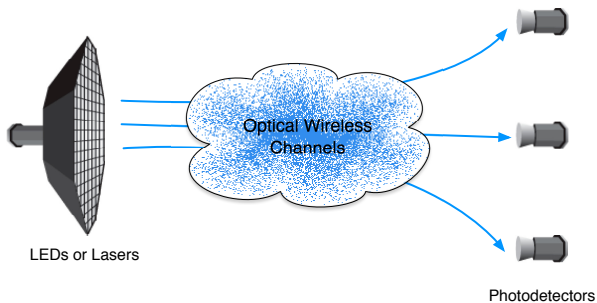
Jan. 7th, 2020

Free-Space Optical Wireless Communication



Intensity Modulation-Direct Detection Communication
Signal proportional to intensity/power

Free-Space Optical Wireless Communication



Multiple-Input Multiple-Output (MIMO) Channel
Assume non-coherent superpositioning

Free-Space Optical Intensity Channel

- Transmitter equipped with n_T LEDs
- Receiver with n_R photodetectors
- Channel output

$$\mathbf{Y} = \mathbf{H}\mathbf{x} + \mathbf{Z}$$

- \mathbf{H} channel matrix with nonnegative entries

$$\mathbf{H} := [\mathbf{h}_1, \mathbf{h}_2, \dots, \mathbf{h}_{n_T}] \in \mathbb{R}^{n_R \times n_T}$$

- \mathbf{Z} Gaussian noise

$$\mathbf{Z} \sim \mathcal{N}(0, \mathbf{I})$$

Constraints on \mathbf{X}

- Nonnegativity and peak-power constraint:

$$X_k \in [0, A], \quad \forall k \in \{1, \dots, n_T\}$$

- Total average-power constraint:

$$E[\|\mathbf{X}\|_1] \leq \alpha A, \quad \alpha \in \left(0, \frac{n_T}{2}\right]$$

- Channel: $\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{Z}$
- Capacity:

$$C_H(A, \alpha A) = \max_{P_{\mathbf{X}} \text{ s.t. (C1) \& (C2)}} I(\mathbf{X}; \mathbf{Y})$$

$$(C1) \quad \mathbf{X} \in [0, A]^{n_T}$$

$$(C2) \quad E[\|\mathbf{X}\|_1] \leq \alpha A$$

- Capacity-achieving input distribution discrete [Smith'69], [Fahs&Abou-Faycal'18]

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$$C_H(A, \alpha A) = \max_{P_{\mathbf{X}} \text{ s.t. (C1) \& (C2)}} h(\mathbf{H}\mathbf{X} + \mathbf{Z}) - h(\mathbf{Z})$$

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$$R_Y(y) = \begin{cases} \beta \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} & \text{if } y < 0, \\ (1 - \beta) \cdot \frac{1}{A} \cdot \frac{\mu}{1 - e^{-\mu}} \cdot e^{-\frac{\mu y}{A}}, & \text{if } y \in [0, A], \\ \beta \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{(y-A)^2}{2}} & \text{if } y > A. \end{cases}$$

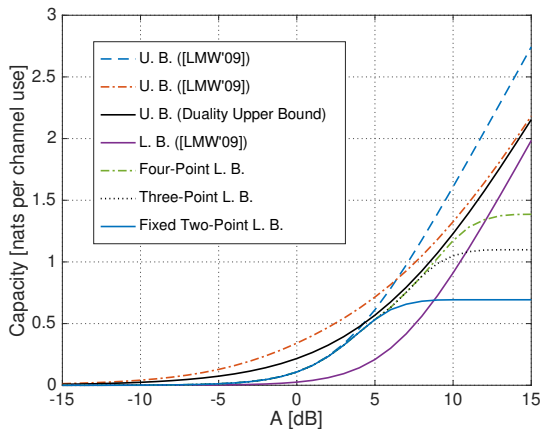
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- Only peak-power: [McKellips'04],[Thangaraj-Kramer-Böcherer'17], [Rassouli-Clerckx'17]

Numerical Result for a SISO Channel



- Average-to-peak power ratio $\alpha = 0.4$

- Low-SNR capacity [Lapidoth-Moser-W'09]

$$C(A, \alpha A) = \frac{A^2(1 - \alpha)}{2} + o(A^2)$$

- High-SNR capacity [Lapidoth-Moser-W'02]

$$C(A, \alpha A) = \frac{1}{2} \log \frac{A^2}{2\pi e} - (1 - \alpha)\mu^* + \log(1 - \alpha\mu^*) + o(1)$$

Previous Results on MIMO channels

- n -by- n full-rank channel matrix:
 - Rx inverts channel matrix and Tx independently codes over parallel channels
 - Achieves high-SNR capacity
 - [Chaaban-Rezki-Alouini'17],[Dytso-Goldenbaum-Shamai-Poor'17],[Moser-Mylonakis-Wang-W'17]
- $n_R \geq n_T$: Rx performs SVD decomposition and ignores some outputs
- $n_T > n_R \geq 1$: Linear precoding matrix like for beamforming? [Chaaban-Rezki-Alouini'18]
- There are better solutions for $n_T > n_R$! [Moser-Wang-W'17]

MISO Channel ($n_T > n_R = 1$)

- Channel: $Y = \mathbf{h}^T \mathbf{X} + Z$
- Assume $\mathbf{h} = (h_1, \dots, h_{n_T})$ with $h_1 \geq h_2 \geq h_3 \geq \dots \geq h_{n_T}$
- Capacity: $C(A, \alpha A) = \max_{P_X} h(\mathbf{h}^T \mathbf{X} + Z) - h(Z)$
s.t.
 - (c1) $X_i \in [0, A], \quad i \in \{1, \dots, n_T\},$
 - (c2) $\sum_{i=1}^{n_T} E[X_i] \leq \alpha A$

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$$(c1\bar{X}) \quad \bar{X} \in \left[0, \sum_{k=1}^{n_T} h_k A \right],$$

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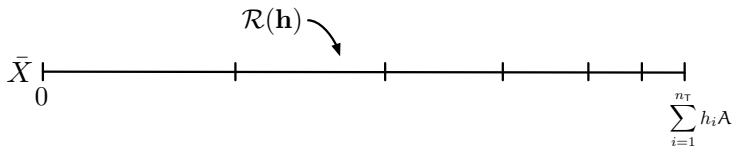
$$\text{s.t.} \\ (c1\bar{X}) \quad \bar{X} \in \left[0, \sum_{k=1}^{n_T} h_k A \right],$$

$$(c2\bar{X}) \quad \sum_{i=1}^{n_T} E[X_i] \leq \alpha A \quad ? \text{ in terms of } \bar{X}$$

MISO Channel ($n_T > n_R = 1$)

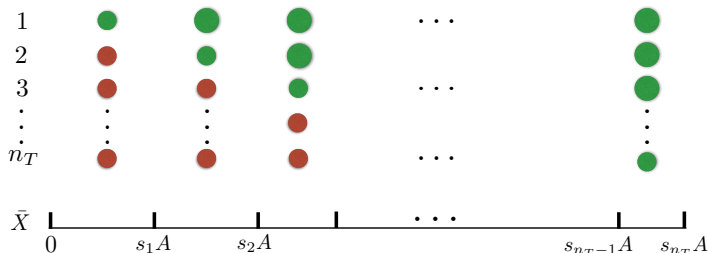
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(c1 \bar{X}) $\bar{X} \in \left[0, \sum_{k=1}^{n_T} h_k A\right]$,
(c2 \bar{X}) $\leq \alpha A$? in terms of \bar{X}

Restrict to inputs that consume minimum energy!



MISO Minimum-Energy Signaling

- Assume $h_1 \geq h_2 \geq h_3 \geq \dots \geq h_{n_T}$
- Define $s_k := \sum_{i=1}^k h_i$ and $U = k \iff \bar{X} \in [s_{k-1}, s_k)$
- Minimum-energy signaling (reduces $\sum E[X_i]$):



- Average power:

$$\mathbb{E}[\bar{X}] = \sum_{i=1}^{n_T} \Pr[U = i] \left(\frac{\mathbb{E}[\bar{X} | U = i] - A s_{i-1}}{h_i} + (i-1)A \right)$$

Equivalent MISO Capacity Expression in Terms of \bar{X}

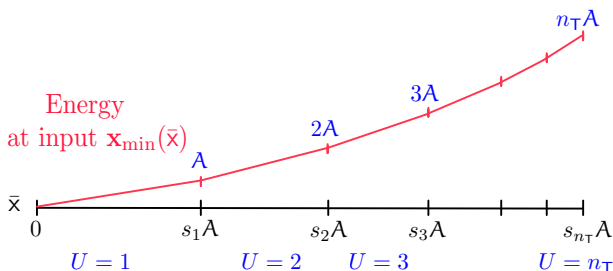
Theorem

$$C_h(A, \alpha A) = \max_{P_{\bar{X}}} I(\bar{X}; Y)$$

subject to:

$$(C1) \quad \bar{X} \in [0, s_{n_T} A]$$

$$(C2) \quad \sum_{i=1}^{n_T} \Pr[U = i] \left(\frac{\mathbb{E}[\bar{X} | U = i] - A s_{i-1}}{h_i} + (i-1)A \right) \leq \alpha A$$



- Entropy-Power Inequality (EPI)

$$\begin{aligned} C &\geq \frac{1}{2} \max_{P_{\bar{X}} \text{ s.t. } (c1\bar{X}) \& (c2\bar{X})} \log \left(1 + \frac{e^{2h(\bar{X})}}{2\pi e} \right) \\ &= \frac{1}{2} \max_{P_{\bar{X}} \text{ s.t. } (c1\bar{X}) \& (c2\bar{X})} \log \left(1 + \frac{e^{2(H(U)+h(\bar{X}|U))}}{2\pi e} \right) \end{aligned}$$

- For each $U = i$, maximize $h(\bar{X}|U = i)$ s.t. $E[\bar{X}|U = i] \leq \mu$
→ uniform or truncated exponential distribution
- Optimize over P_U, μ

MISO Capacity Upper Bound

- \bar{X}^*, Y^* the capacity-achieving input and output and

$$(U = i) \implies (\bar{X}^* \in (s_{i-1}, s_i])$$

Then: $C \leq I(\bar{X}^*; Y^*, U) = H(U) + I(\bar{X}^*; Y^*|U)$

$$= H(P_U) + \sum_{i=1}^{n_T} P_U(i) \cdot I(\bar{X}^*; Y^*|U = i)$$

- Given $U = i$, $\bar{X}^* \mapsto Y^*$ is a single-antenna channel with a linear power constraint \Rightarrow
apply previous UBs to each $I(\bar{X}^*; Y^*|U = i)$
- Choose $E[\bar{X}^*|U = i] = \mu, \forall i$ and optimize over P_U, μ

MIMO Channel Capacity ($n_T > n_R$)

- Channel: $\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{Z}$
- Capacity: $C = \max_{P_{\mathbf{X}}} h(\mathbf{H}\mathbf{X} + \mathbf{Z}) - h(\mathbf{Z})$
s.t.

$$(c1) \quad \mathbf{X} \in [0, A]^{n_T}$$

$$(c2) \quad E[\|\mathbf{X}\|_1] \leq \alpha A$$

Recall $\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \dots, \mathbf{h}_{n_T}]$

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s.t.

$$(c1\bar{\mathbf{X}}) \quad \bar{\mathbf{X}} \in \mathcal{R}(\mathbf{H}) := \left\{ \sum_{k=1}^{n_T} x_k \mathbf{h}_k : x_1, \dots, x_{n_T} \in [0, A] \right\}$$

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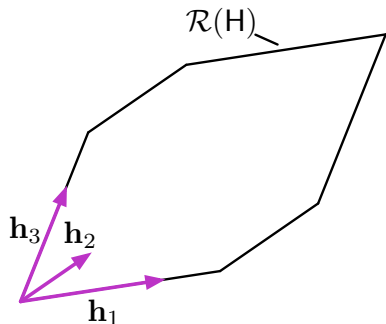
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Restrict to minimum-energy signaling: $\mathbf{x}_{\min}(\bar{\mathbf{x}}) := \underset{\mathbf{x}: \mathbf{H}\mathbf{x}=\bar{\mathbf{x}}}{\operatorname{argmin}} \|\mathbf{x}\|_1$

Recall $\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \dots, \mathbf{h}_{n_T}]$

Example of 2×3 MIMO Minimum-Energy Signaling

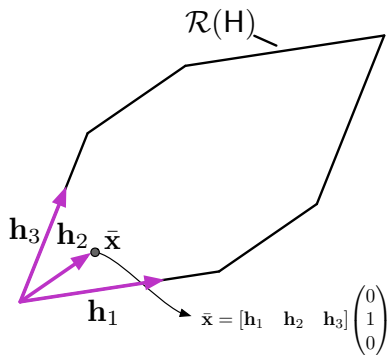
For each $\bar{\mathbf{x}} \in \mathcal{R}(\mathbf{H})$: $\mathbf{x}_{\min}(\bar{\mathbf{x}}) := \operatorname{argmin}_{\mathbf{x}: \mathbf{H}\mathbf{x}=\bar{\mathbf{x}}} \|\mathbf{x}\|_1$



$$\mathbf{H} = [\mathbf{h}_1 \ \mathbf{h}_2 \ \mathbf{h}_3] = \begin{pmatrix} 3 & 1.75 & 1 \\ 0.5 & 1 & 3 \end{pmatrix}$$

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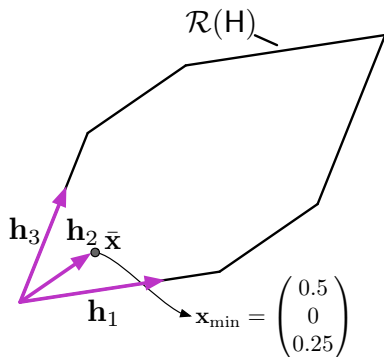
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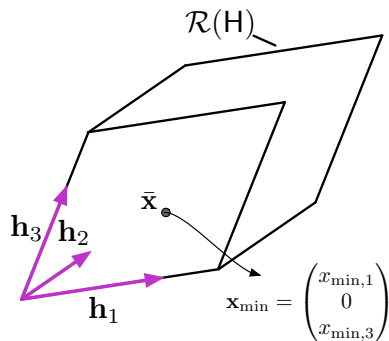
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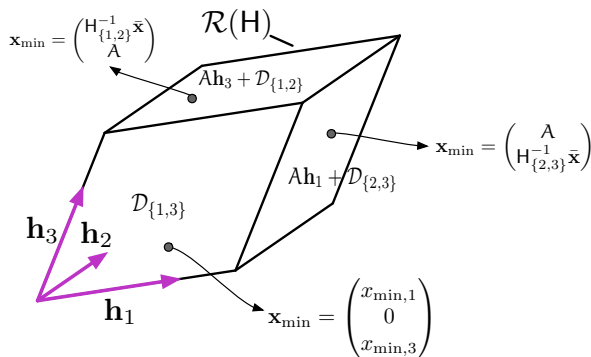
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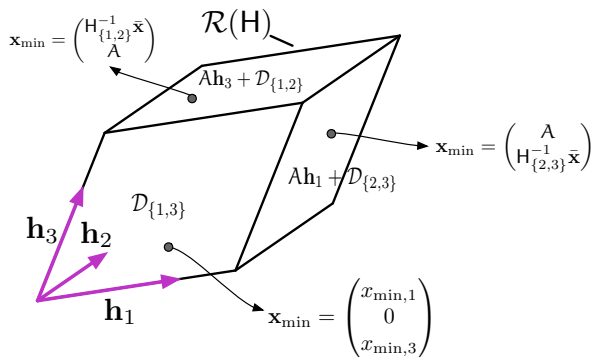
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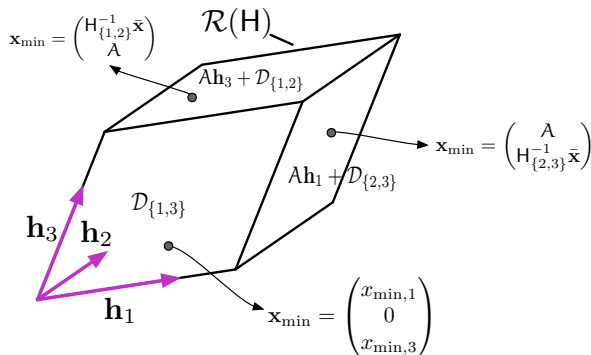
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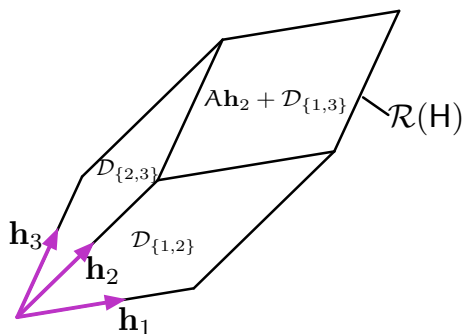


$$\mathbf{H} = [\mathbf{h}_1 \ \mathbf{h}_2 \ \mathbf{h}_3] = \begin{pmatrix} 3 & 1.75 & 1 \\ 0.5 & 1 & 3 \end{pmatrix}$$

In each parallelepiped only two antennas are used for signaling \rightarrow full-rank 2×2 MIMO channel

Example of 2×3 MIMO Minimum-Energy Signaling

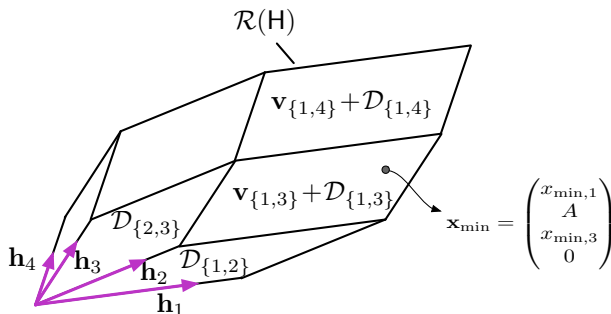
Another 2×3 MIMO channel:



$$\mathbf{H} = [\mathbf{h}_1 \ \mathbf{h}_2 \ \mathbf{h}_3] = \begin{pmatrix} 2.5 & 2 & 1 \\ 1 & 2 & 2 \end{pmatrix}$$

Example of 2×4 MIMO Minimum-Energy Signaling

A 2×4 MIMO channel:



$$\mathbf{H} = [\mathbf{h}_1 \ \mathbf{h}_2 \ \mathbf{h}_3 \ \mathbf{h}_4] = \begin{pmatrix} 7 & 5 & 2 & 1 \\ 1 & 2 & 2.9 & 3 \end{pmatrix}$$

Minimum-Energy Signaling for $n_R \times n_T$ MIMO Channels

- Minimum-energy signaling partitions $\mathcal{R}(\mathbf{H})$ into $\binom{n_T}{n_R}$ parallelepipeds, each one spanned by one subset of n_R channel vectors
- In each parallelepiped $\mathcal{D}_{\mathcal{I}}$ only antennas in \mathcal{I} are used for signaling, the others are set 0 or $\Lambda \Rightarrow$ an $n_R \times n_R$ full-rank MIMO channel
- Arrangement of parallelepipeds $\{\mathcal{D}_{\mathcal{I}}\}$ depends on the channel matrix and is determined by $\{\mathbf{v}_{\mathcal{I}}\}$:

$$\mathbf{v}_{\mathcal{I}} := \Lambda \sum_{j \in \mathcal{I}^c} \mathbb{I}(\mathbf{1}_{n_R}^T \mathbf{H}_{\mathcal{I}}^{-1} \mathbf{h}_j > 1) \mathbf{h}_j$$

with

$$\mathbf{H}_{\mathcal{I}} := [\mathbf{h}_i : i \in \mathcal{I}]$$

Minimum-Energy Signaling: Proof based on KKT

■ Lagrangean: $\mathcal{L} = \|\mathbf{x}\|_1 - \boldsymbol{\mu}^\top \mathbf{x} + \boldsymbol{\nu}^\top (\mathbf{x} - \Lambda) - \boldsymbol{\lambda}^\top (H\mathbf{x} - \bar{\mathbf{x}})$

■ KKT conditions:

$$\mathbf{1}_{n_T} - \boldsymbol{\mu}^* + \boldsymbol{\nu}^* - H^\top \boldsymbol{\lambda}^* = \mathbf{0}$$

$$H\mathbf{x}^* - \bar{\mathbf{x}} = \mathbf{0}$$

$$\mu_i^* x_i^* = 0, \quad i \in \{1, \dots, n_T\},$$

$$\nu_i^* (x_i^* - \Lambda) = 0, \quad i \in \{1, \dots, n_T\},$$

- KKT conditions:

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$$\mathbf{H} \mathbf{x}^* - \bar{\mathbf{x}} = \mathbf{0}$$

$$\mu_i^* x_i^* = 0, \quad i \in \{1, \dots, n_T\},$$

$$\nu_i^* (x_i^* - A) = 0, \quad i \in \{1, \dots, n_T\},$$

- Set $i \in \mathcal{I} \iff x_i^* \in (0, A)$:

$$\mu_{\mathcal{I}} = \nu_{\mathcal{I}} = \mathbf{0} \Rightarrow \mathbf{H}_{\mathcal{I}}^T \boldsymbol{\lambda}^* = \mathbf{1}_{|\mathcal{I}|} \Rightarrow \boldsymbol{\lambda}^* = \mathbf{H}_{\mathcal{I}}^{-T} \mathbf{1}_{|\mathcal{I}|}.$$

- KKT conditions:

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$$\mu_i^* x_i^* = 0, \quad i \in \{1, \dots, n_T\},$$

$$\nu_i^* (x_i^* - A) = 0, \quad i \in \{1, \dots, n_T\},$$

- Set $i \in \mathcal{I} \iff x_i^* \in (0, A)$; restrict to $\text{rank}(\mathbf{H}_{\mathcal{I}}) = n_R$!:

$$\mu_{\mathcal{I}} = \nu_{\mathcal{I}} = \mathbf{0} \Rightarrow \mathbf{H}_{\mathcal{I}}^T \boldsymbol{\lambda}^* = \mathbf{1}_{|\mathcal{I}|} \Rightarrow \boldsymbol{\lambda}^* = \mathbf{H}_{\mathcal{I}}^{-T} \mathbf{1}_{|\mathcal{I}|}.$$

Minimum-Energy Signaling: Proof based on KKT

- KKT conditions:

$$\mathbf{1}_{n_T} - \boldsymbol{\mu}^* + \boldsymbol{\nu}^* - \mathbf{H}^T \boldsymbol{\lambda}^* = \mathbf{0}$$

$$\mathbf{H} \mathbf{x}^* - \bar{\mathbf{x}} = \mathbf{0}$$

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- Optimal inputs $\mathbf{x}_{\mathcal{I}}^* = \mathbf{H}_{\mathcal{I}}^{-1} \left(\bar{\mathbf{x}} - \underbrace{\sum_{j \in \mathcal{I}^c} x_j^* \mathbf{h}_j}_{\mathbf{v}_{\mathcal{I}}} \right)$

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$$\mu_{\mathcal{I}} = \nu_{\mathcal{I}} = \mathbf{0} \Rightarrow \mathbf{H}_{\mathcal{I}}^T \boldsymbol{\lambda}^* = \mathbf{1}_{|\mathcal{I}|} \Rightarrow \boldsymbol{\lambda}^* = \mathbf{H}_{\mathcal{I}}^{-T} \mathbf{1}_{|\mathcal{I}|}.$$

- Optimal inputs x_j^* for $j \in \mathcal{I}^c$:

$$1 - \mathbf{h}_j^T \mathbf{H}_{\mathcal{I}}^{-T} \mathbf{1}_{|\mathcal{I}|} = \mu_j^* \cdot \mathbb{I}\{x_j^* = 0\} - \nu_j^* \cdot \mathbb{I}\{x_j^* = A\}$$

$$\mu_j^*, \nu_j^* \geq 0 \rightarrow \text{value of } x_j^* \text{ determined by } \text{sign}(1 - \mathbf{h}_j^T \mathbf{H}_{\mathcal{I}}^{-T} \mathbf{1}_{|\mathcal{I}|})$$

Equivalent Capacity Expression in terms of $\bar{\mathbf{X}}$

Theorem (Equivalent Capacity Expression)

The MIMO capacity satisfies

$$C = \max_{P_{\bar{\mathbf{X}}}} I(\bar{\mathbf{X}}; \mathbf{Y}),$$

where $P_{\bar{\mathbf{X}}}$ over $\mathcal{R}(\mathbf{H})$ and subject to the power constraint:

$$\sum_{\substack{\mathcal{I} \subseteq \{1, 2, \dots, n_T\} \\ |\mathcal{I}| = n_R}} p_{\mathcal{I}} \cdot \left(\|\mathbf{H}_{\mathcal{I}}^{-1} (\mathbb{E}[\bar{\mathbf{X}} | \mathcal{I}] - \mathbf{v}_{\mathcal{I}})\|_1 + \|\mathbf{v}_{\mathcal{I}}\|_1 \right) \leq \alpha A$$

with

$$p_{\mathcal{I}} = \Pr(\bar{\mathbf{X}} \in (\mathbf{v}_{\mathcal{I}} + \mathcal{D}_{\mathcal{I}}))$$

$$\mathbf{v}_{\mathcal{I}} = A \cdot \sum_{j \in \mathcal{I}^c} \mathbb{I}(\mathbf{1}_{n_R}^T \mathbf{H}_{\mathcal{I}}^{-1} \mathbf{h}_j > 1) \cdot \mathbf{h}_j$$

- $\bar{\mathbf{X}}^*, \mathbf{Y}^*$ the capacity-achieving input and output and

$$(U = \mathcal{I}) \implies (\bar{\mathbf{X}}^* \in (\mathbf{v}_{\mathcal{I}} + \mathcal{D}_{\mathcal{I}}))$$

Then: $C \leq I(\bar{\mathbf{X}}^*; \mathbf{Y}^*, U^*) = H(U^*) + I(\bar{\mathbf{X}}^*; \mathbf{Y}^* | U^*)$

$$= H(\{p_{\mathcal{I}}^*\}) + \sum_{\substack{\mathcal{I} \subseteq \{1, 2, \dots, n_T\} \\ |\mathcal{I}| = n_R}} p_{\mathcal{I}} \cdot I(\bar{\mathbf{X}}^*; \mathbf{Y}^* | U^* = \mathcal{I})$$

- Given $U = \mathcal{I}$, $\mathbf{X}^* \mapsto \mathbf{Y}^*$ is an $n_R \times n_R$ MIMO with invertible channel matrix \rightarrow use previous UBs
- For duality bound: uniform or rotated truncated exponential distribution with Gaussian tails

- Entropy-Power Inequality (EPI)

$$\begin{aligned} C &\geq \max_{P_{\bar{\mathbf{X}}} \text{ s.t. } (c1\bar{\mathbf{X}}) \& (c2\bar{\mathbf{X}})} \frac{1}{2} \log \left(1 + \frac{e^{2h(\bar{\mathbf{X}})}}{2\pi e} \right) \\ &= \max_{P_{\bar{\mathbf{X}}} \text{ s.t. } (c1\bar{\mathbf{X}}) \& (c2\bar{\mathbf{X}})} \frac{1}{2} \log \left(1 + \frac{e^{2(H(U)+h(\bar{\mathbf{X}}|U))}}{2\pi e} \right) \end{aligned}$$

- For each $U = i$ choose $P_{\bar{\mathbf{X}}|U=i}$ to maximize $h(\bar{\mathbf{X}}|U = i)$
→ uniform or rotated truncated exponential distribution
- Numerically optimize over P_U

Theorem (High-SNR Asymptotics)

For $\alpha \geq \alpha_{\text{th}}(\mathbf{H})$,

$$\lim_{A \rightarrow \infty} \{C - n_R \log A\} = \frac{1}{2} \log \left(\frac{V_H^2}{(2\pi e)^{n_R}} \right)$$

For $\alpha < \alpha_{\text{th}}(\mathbf{H})$,

$$\lim_{A \rightarrow \infty} \{C - n_R \log A\} = \frac{1}{2} \log \left(\frac{V_H^2}{(2\pi e)^{n_R}} \right) + \nu$$

with

$$V_H := \text{vol}(\mathcal{R}(\mathbf{H}))$$

$$\nu := \sup_{\lambda \in (\max\{0, \frac{n_R}{2} + \alpha - \alpha_{\text{th}}\}, \min\{\frac{n_R}{2}, \alpha\})} \left\{ n_R \left(1 - \log \frac{\mu}{1-e^{-\mu}} - \frac{\mu e^{-\mu}}{1-e^{-\mu}} \right) - \inf_{\mathbf{p}} D(\mathbf{p} \parallel \mathbf{q}) \right\}$$

- At high SNR, average-power constraint is **not active** for $\alpha > \alpha_{\text{th}}$

- The covariance matrix of $\bar{\mathbf{X}} = \mathbf{H}\mathbf{X}$:

$$\mathbf{K}_{\bar{\mathbf{X}}\bar{\mathbf{X}}} \triangleq \mathbb{E}[(\bar{\mathbf{X}} - \mathbb{E}[\bar{\mathbf{X}}])(\bar{\mathbf{X}} - \mathbb{E}[\bar{\mathbf{X}}])^T]$$

Lemma

For an arbitrary α ,

$$C \leq \frac{n_R}{2} \log \left(1 + \frac{1}{n_R} \max_{P_{\bar{\mathbf{X}}}} \text{tr}(\mathbf{K}_{\bar{\mathbf{X}}\bar{\mathbf{X}}}) \right)$$

- Maximum-Variance Upper Bound

$$C \leq \frac{n_R}{2} \log \left(1 + \frac{1}{n_R} \max_{P_{\bar{\mathbf{x}}}} \text{tr} \left(K_{\bar{\mathbf{x}}\bar{\mathbf{x}}} \right) \right)$$

- Maximum-Variance Lower Bound [Prelov-van der Meulen'04]

$$C \geq \frac{1}{2} \log \max_{P_{\bar{\mathbf{x}}}} \text{tr} \left(K_{\bar{\mathbf{x}}\bar{\mathbf{x}}} \right) + o(A^2)$$

- Low-SNR Capacity Slope [Chaaban-Rezki-Alouini'18]

$$\lim_{A \downarrow 0} \frac{C}{A^2} = \frac{1}{2} \log \max_{P_{\bar{\mathbf{x}}}} \text{tr} \left(K_{\bar{\mathbf{x}}\bar{\mathbf{x}}} \right)$$

- An optimal input to the maximum trace uses for each component of \mathbf{X} only the values 0 and A

$$X_i \in \{0, A\} \quad \text{with probability 1,} \quad i = 1, \dots, n_T$$

- An optimal input is over a set $\{\mathbf{x}_1^*, \mathbf{x}_2^*, \dots\}$ satisfying

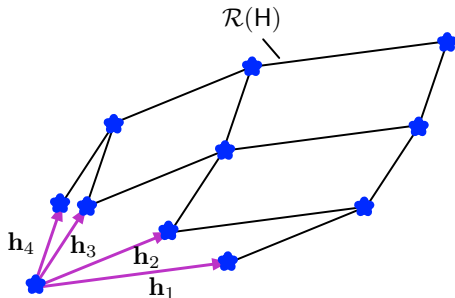
$$x_{k,l}^* \leq x_{k',l}^* \quad \text{for all } k < k', \ell = 1, \dots, n_T$$

e.g.

$$(0, 0, 0, 0, 0); \quad (0, A, 0, 0, 0); \quad (0, A, 0, A, 0); \quad (0, A, 0, A, A)$$

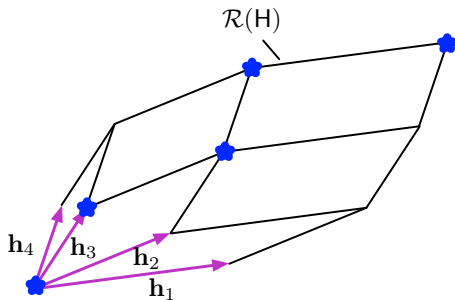
New Properties of $\max_{P_{\bar{x}}} \text{tr}(K_{\bar{x}\bar{x}})$

- By the optimality of minimum-energy signaling, we can restrict to **corner points** of parallelepipeds



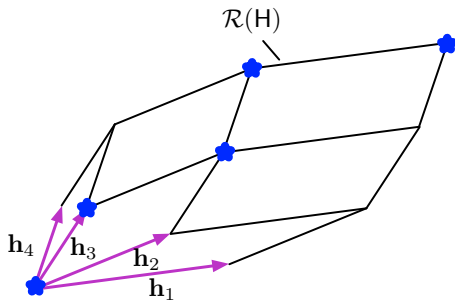
New Properties of $\max_{P_{\bar{x}}} \text{tr}(K_{\bar{x}\bar{x}})$

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- Examining the KKT conditions: under mild technical conditions $\rightarrow n_R + 2$ mass points suffice



New Properties of $\max_{P_{\bar{x}}} \text{tr}(K_{\bar{x}\bar{x}})$

- By the optimality of minimum-energy signaling, we can restrict to **corner points** of parallelepipeds
- Examining the KKT conditions: under mild technical conditions $\rightarrow n_R + 2$ mass points suffice



Significantly reduce numerical computation of $\max \text{tr}(K_{\bar{x}\bar{x}})$

Numerical Examples on Maximum-Variance Signaling

channel matrix	α	$\max_{P_{\mathbf{x}}} \text{tr}(K_{\bar{\mathbf{x}}\bar{\mathbf{x}}})$	$P_{\mathbf{x}}: \max_{P_{\mathbf{x}}} \text{tr}(K_{\bar{\mathbf{x}}\bar{\mathbf{x}}})$
$H = \begin{pmatrix} 1.3 & 0.6 & 1 & 0.1 \\ 2.1 & 4.5 & 0.7 & 0.5 \end{pmatrix}$	1.5	$16.3687A^2$	$P_{\mathbf{x}}(0, 0, 0, 0) = 0.625,$ $P_{\mathbf{x}}(A, A, A, A) = 0.375$
	0.9	$12.957A^2$	$P_{\mathbf{x}}(0, 0, 0, 0) = 0.7,$ $P_{\mathbf{x}}(A, A, A, 0) = 0.3$
	0.6	$9.9575A^2$	$P_{\mathbf{x}}(0, 0, 0, 0) = 0.7438,$ $P_{\mathbf{x}}(A, A, 0, 0) = 0.1687,$ $P_{\mathbf{x}}(A, A, A, 0) = 0.0875$
	0.3	$6.0142A^2$	$P_{\mathbf{x}}(0, 0, 0, 0) = 0.85,$ $P_{\mathbf{x}}(A, A, 0, 0) = 0.15$
$H = \begin{pmatrix} 0.9 & 3.2 & 1 & 2.1 \\ 0.5 & 3.5 & 1.7 & 2.5 \\ 0.7 & 1.1 & 1.1 & 1.3 \end{pmatrix}$	0.9	$23.8405A^2$	$P_{\mathbf{x}}(0, 0, 0, 0) = 0.7755,$ $P_{\mathbf{x}}(A, A, A, A) = 0.2245$

- Minimum-energy signaling: decompose the original channel into a set of almost parallel channels. Each one an $n_R \times n_R$ MIMO channel with an invertible channel matrix
- New upper bounds by using duality capacity expression, and lower bounds by using the EPI. They match at high-SNR, establishing the high-SNR asymptotic capacity
- At low-SNR, a computationally easier way to evaluate the low-SNR capacity slope

Channel Model

$$\mathbf{Y}_t[n] = \mathbb{H}_t \mathbf{x}_t[n] + \mathbf{Z}_t[n]$$

- $t \in \{1, 2, \dots, B\}$ the block index, B the number of blocks
- $n \in \{1, 2, \dots, N\}$ the symbol index, N the block length
- Channel input vector $\mathbf{x}_t[n]$

$$(C1) \quad \mathbf{x}_t[n] \in [0, A]^{n_T} \quad \forall n \in \{1, 2, \dots, N\}$$

$$(C2) \quad \frac{1}{N} \mathbb{E} \left[\sum_{n=1}^N \|\mathbf{x}_t[n]\|_1 \right] \leq \alpha A \quad \forall t \in \{1, 2, \dots, B\}$$

- \mathbb{H}_t a random $n_R \times n_T$ matrix, fixed in one block, i.i.d across blocks

Channel State Information (CSI)

- Ergodic Capacity
 - The highest achievable rate when $B \rightarrow \infty$
- Availability of CSI
 - Receiver always has perfect CSI
 - Transmitter has **no CSI**, **perfect CSI**, and **limited CSI**

NO CSI at the Transmitter

- With no CSI at the transmitter, the choice of $P_{\mathbf{X}}$ is independent of \mathbf{H}

Theorem

If the transmitter has no CSI, then

$$C_{\mathbb{H}} = \max_{P_{\mathbf{X}}} E_{\mathbb{H}} [I(\mathbf{X}; \mathbb{H}\mathbf{X} + \mathbf{Z} | \mathbb{H} = \mathbf{H})]$$

- A precoding strategy:

$$\mathbf{X} = \mathbf{G}\mathbf{V}$$

\mathbf{G} is an $n_T \times n_R$ matrix, and \mathbf{V} the n_R -dimensional random vector exponentially distributed with density

$$f(\mathbf{v}) = \frac{1}{A^{n_R}} \left(\frac{\mu}{1 - e^{-\mu}} \right)^{n_R} e^{-\frac{\mu \|\mathbf{v}\|_1}{A}}, \quad \mathbf{v} \in [0, A]^{n_R}$$

Theorem

If the transmitter has no CSI, then

$$C_{\mathbb{H}} \geq \frac{1}{2} \sup_{\lambda \in (0, \frac{n_{\mathbb{R}}}{2})} \sup_{\mathbf{G}} \mathbb{E}_{\mathbb{H}} \left[\log_2 \left(1 + \frac{A^{2n_{\mathbb{R}}} (\det \mathbb{H} \mathbf{G})^2 e^{2\nu}}{(2\pi e)^{n_{\mathbb{R}}}} \right) \right]$$

the sup. over all $n_{\mathbb{T}} \times n_{\mathbb{R}}$ precoding matrices \mathbf{G} :

- nonnegative entries
- $\text{rank}(\mathbf{G}) = n_{\mathbb{R}}$
- $\|\mathbf{G}\|_1 \leq \alpha/\lambda$, and with row vectors satisfying $\|\mathbf{g}_i\|_1 \leq 1$, $\forall i \in \{1, \dots, n_{\mathbb{T}}\}$

and ν is defined as

$$\nu \triangleq n_{\mathbb{R}} \left(1 - \log_2 \frac{\mu}{1 - e^{-\mu}} - \frac{\mu e^{-\mu}}{1 - e^{-\mu}} \right)$$

- With perfect CSI at the transmitter, the choice of $P_{\mathbf{X}}$ depends on the CSI

Theorem

If the transmitter has perfect CSI, then

$$C_{\mathbb{H}} = E_{\mathbb{H}} \left[\max_{P_{\mathbf{X}|\mathbb{H}=\mathbf{H}}} I(\mathbf{X}; \bar{\mathbf{X}} + \mathbf{Z} | \mathbb{H} = \mathbf{H}) \right]$$

- For each channel realization $\mathbb{H} = \mathbf{H}$, we use bounds from MIMO case
- Signaling exploits minimum-energy signaling

- By a rate-limited feedback link, at the beginning of each block, the receiver sends a function of \mathbb{H} , $\mathcal{F}(\mathbb{H})$, back to the transmitter
- The choice of $P_{\mathbf{X}}$ depends on $\mathcal{F}(\mathbb{H})$

Theorem

The capacity $C_{\mathbb{H},\mathcal{F}}$ of a channel with limited CSI $\mathcal{F}(\mathbb{H})$ at the transmitter is:

$$C_{\mathbb{H},\mathcal{F}} = E_{\mathbb{H}} \left[\max_{P_{\mathbf{X}|\mathcal{F}(\mathbb{H})}} I(\mathbf{X}; \mathbf{Y} | \mathbb{H} = \mathbf{H}) \right]$$

- Receiver feeds back

$$R_{\text{FB}} = (n_{\text{T}} - n_{\text{R}}) \cdot \binom{n_{\text{T}}}{n_{\text{R}}}$$

bits per channel block

- The R_{FB} bits describes the binary values of $n_{\text{T}} - n_{\text{R}}$ antennas not used for signaling in each parallelepiped in the minimum-energy signaling strategy
- The input distribution in each parallelepiped are chosen to be a truncated exponential distribution satisfying the power constraint

Theorem

For the limited CSI function \mathcal{F} :

$$C_{\mathbb{H}, \mathcal{F}} \geq \mathbb{E}_{\mathcal{F}(\mathbb{H})} \left[\sup_{\lambda \in (0, \frac{n_R}{2})} \sup_{\mathbf{p}} \mathbb{E}_{\mathbb{H}|\mathcal{F}} \left[\frac{1}{2} \log \left(1 + \frac{A^{2n_R} V_H^2 e^{2\nu^*}}{(2\pi e)^{n_R}} \right) \right] \right]$$

where

$$\nu^* \triangleq n_R \left(1 - \log_2 \frac{\mu}{1 - e^{-\mu}} - \frac{\mu e^{-\mu}}{1 - e^{-\mu}} \right) - D(\mathbf{p} \parallel \mathbf{q})$$

where the supremum over \mathbf{p} is over all PMFs satisfying

$$\sum_{I \in \mathcal{U}} p_I s_I = \alpha - \lambda.$$

Numerical Result for a 1×3 Channel

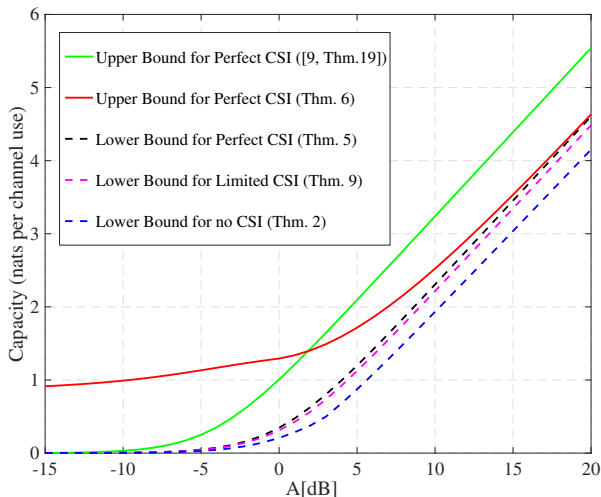


Figure 1: A 1×3 MISO channel, where the entries in \mathbb{H} follow a Gamma-Gamma distribution.

- Lower bounds presented for the capacities without CSI, with perfect CSI, and with limited CSI
- For perfect CSI, the lower bound asymptotically tight at high SNR
- For limited CSI, the lower bound is close to the one with perfect CSI, but with only $(n_T - n_R) \binom{n_T}{n_R}$ bits of feedback in each block

- Minimum-energy signaling: decompose $\mathcal{R}(\mathbf{H})$ into $\binom{n_T}{n_R}$ n_R -dim. parallelepipeds, and use a different subset of n_R antennas for signaling in each parallelepiped
- Several upper bounds by duality-based capacity expression and lower bounds by the EPI
- High-and low-SNR asymptotic capacity
- With limited bits of channel state feedback, the perfect CSI capacity can be well approximated