

On Achievable Rates of MIMO Systems with Nonlinear Receivers

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Agenda

- 1 Introduction
- 2 System Model
- 3 Rate Computation
- 4 Simulation Results
- 5 Conclusions

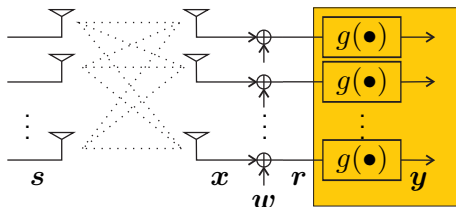
- MIMO systems achieve high rate gains.
- Multiple antennas = multiple receiver chains.
- **Expensive** and **power consuming** receiver circuitry (mixers, frequency synthesis, PLL's, linear amplifiers etc.).
- Applications like sensor networks require very energy-efficient and cheap solutions in order to maximize lifetime.
- **Amplitude** and **phase** detection are known as low-cost/low-power alternatives to receiver design.
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- We assume that channel knowledge is available at the receiver.
- In a Time Division Duplex system, CSI can be signaled from the more complex access point to the node.
- The node could employ a linear receiver for channel estimation and switch to a nonlinear receiver for receiving data.
- For phase detection, it is possible to estimate the channel amplitude from the variation of the phase samples [Althaus, Wittneben].

System Model



(See flip board!)

- Linear model: $\mathbf{r} = \mathbf{H}\mathbf{s} + \mathbf{w}$.
- The channel matrix \mathbf{H} has i.i.d. $\mathcal{CN}(0, 1)$ entries.
- Transmit signal — $\mathbf{s} \sim \mathcal{CN}(\mathbf{0}, \sigma_s^2 \mathbf{I}_{N_T})$.
- AWG noise — $\mathbf{w} \sim \mathcal{CN}(\mathbf{0}, \sigma_w^2 \mathbf{I}_{N_R})$.
- The nonlinear operator g extracts either the phase or the amplitude of \mathbf{r} .

Capacity of linear MIMO System [Telatar, Foschini-Gans]

$$C_{\text{lin}} = \mathbb{E}_{\mathbf{H}} \left[\log \det \left(\mathbf{I}_{N_{\text{R}}} + \frac{\text{SNR}}{N_{\text{T}}} \mathbf{H} \mathbf{H}^{\text{H}} \right) \right].$$

- Average SNR per receive antenna

$$\text{SNR} = \frac{\text{tr}(\mathbf{s} \mathbf{s}^{\text{H}})}{\sigma_w^2} = \frac{N_{\text{T}} \sigma_s^2}{\sigma_w^2}.$$

- Capacity scales with $N_{\text{min}} = \min(N_{\text{T}}, N_{\text{R}})$ at high SNR

$$C_{\text{lin}} \simeq N_{\text{min}} \log \frac{\text{SNR}}{N_{\text{T}}} + \sum_{i=1}^{N_{\text{min}}} \mathbb{E} [\log \lambda_i^2].$$

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Evaluating Nonlinear MIMO Mutual Information (1)

- Mutual Information given the channel realization H

$$I(\mathbf{s}; \mathbf{y}, \mathbf{H}) = \mathbb{E}_{\mathbf{H}}[I(\mathbf{s}; \mathbf{y} | \mathbf{H} = H)].$$

- Chain rule for Mutual Information

$$I(\mathbf{s}, \mathbf{x}; \mathbf{y} | \mathbf{H} = H) = I(\mathbf{x}; \mathbf{y} | \mathbf{H} = H) + I(\mathbf{s}; \mathbf{y} | \mathbf{x}, \mathbf{H} = H),$$

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Evaluating Nonlinear MIMO Mutual Information (2)

- Meanwhile, since $\mathbf{x} = \mathbf{H}\mathbf{s}$

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$$I(\mathbf{s}; \mathbf{y} | \mathbf{H} = H) = I(\mathbf{x}; \mathbf{y} | \mathbf{H} = H).$$

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Evaluating $I(\mathbf{x}; \mathbf{y} | \mathbf{H} = H)$

- Definition

$$\begin{aligned} I(\mathbf{x}; \mathbf{y}) &= h(\mathbf{y}) - h(\mathbf{y} | \mathbf{x}) \\ &= - \int p(\mathbf{y}) \log(p(\mathbf{y})) d\mathbf{y} \\ &\quad + \iint p(\mathbf{x}) p(\mathbf{y} | \mathbf{x}) \log(p(\mathbf{y} | \mathbf{x})) d\mathbf{y} d\mathbf{x}. \end{aligned}$$

- Since $g(\bullet)$ acts element wise

$$p(\mathbf{y} | \mathbf{x}) = \prod_{i=1}^{N_R} p(y_i | x_i).$$

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$h(\mathbf{y}|\mathbf{x})$ — conditional pdf $p(y_i|x_i)$ (1)

- The nonlinear operator for amplitude/phase detection

$$y_{i,\text{ampl.}} = g_{\text{ampl.}}(r_i) = \sqrt{\Re(r_i)^2 + \Im(r_i)^2},$$
$$y_{i,\text{phase}} = g_{\text{phase}}(r_i) = \arg(r_i) = \tan^{-1} \left(\frac{\Im(r_i)}{\Re(r_i)} \right).$$

- Given $x_i, r_i \sim \mathcal{CN}(x_i, \sigma_w^2)$, and the norm of r is Rice distributed

$$p_{\text{ampl.}}(y_i|x_i) = \frac{2y_i}{\sigma_w^2} e^{-\frac{y_i^2 + |x_i|^2}{\sigma_w^2}} I_0 \left(\frac{2y_i|x_i|}{\sigma_w^2} \right).$$

(Use approximation of $I_0(z)$ for high z .)

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$h(\mathbf{y}|\mathbf{x})$ — conditional pdf $p(y_i|x_i)$ (2)

- The phase has a more involved distribution

$$p_{\text{phase}}(\Delta\phi_i|x_i) = \frac{e^{-\rho_i}}{\sigma_w^2} + \sqrt{\frac{\rho_i}{4\pi}} e^{-\rho_i \sin^2 \Delta\phi_i} \cdot \cos \Delta\phi_i \operatorname{erfc}(-\sqrt{\rho_i} \cos \Delta\phi_i),$$

where $\rho_i = \frac{|x_i|^2}{\sigma_w^2}$ and $\Delta\phi_i = y_{i,\text{phase}} - \arg(x_i) \in [0, 2\pi)$.

- We estimate the entropy $h(\mathbf{y}|\mathbf{x})$ with **Monte Carlo (MC) integration**

$$\begin{aligned} h(\mathbf{y}|\mathbf{x}) &= - \iint p(\mathbf{x}, \mathbf{y}) \log(p(\mathbf{y}|\mathbf{x})) d\mathbf{y}d\mathbf{x} \\ &= - \mathbb{E}_{p(\mathbf{x}, \mathbf{y})} [\log(p(\mathbf{y}|\mathbf{x}))] \simeq -\frac{1}{N} \sum_{i=1}^N \log(p(\mathbf{y}_i|x_i)), \end{aligned}$$

where $(x_i, y_i) \sim p(\mathbf{x}, \mathbf{y})$ and we average over N samples.

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$h(\mathbf{y})$ — distribution of \mathbf{y} , $N_R = 1$

- In the MISO case $r = \sum_{i=1}^{N_T} h_{1i}s_i + w$, and for Gaussian input,

$$r \sim \mathcal{CN}(0, \sigma_r^2), \quad \sigma_r^2 = \sum_{i=1}^{N_T} |h_{1i}|^2 \sigma_s^2 + \sigma_w^2.$$

- The norm of r is Rayleigh distributed and the entropy is

$$h(r)[\text{bits}] = \left(1 + \ln \sqrt{\frac{\sigma_r^2}{4}} + \frac{\gamma}{2} \right) \log_2 e$$

- The phase of r is uniform distributed in $[0, 2\pi)$

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$h(\mathbf{y})$ — distribution of \mathbf{y} , $N_R > 1$ (1)

- When $N_R > 1$, the amplitude is a *correlated multivariate Rayleigh distribution* [Mallik, Miller]. For $N_R = 2$, $N_R = 3$

$$p(y_1, y_2) = 4y_1y_2 \det(\mathbf{S}) e^{-(\mathbf{S}_{11}y_1^2 + \mathbf{S}_{22}y_2^2)} I_0(2|\mathbf{S}_{12}|y_1y_2),$$

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where $\mathbf{S} = (\mathbb{E}[\mathbf{r}\mathbf{r}^H])^{-1} = (\sigma_s^2 \mathbf{H}\mathbf{H}^H + \sigma_w^2 \mathbf{I})^{-1}$ and $\chi_{ij} = \arg(\mathbf{S}_{ij})$.

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Entropy of \mathbf{y} in the general case

- In all other cases we estimate the distribution of \mathbf{y} numerically

$$p(\mathbf{y}_i) = \int p(\mathbf{x})p(\mathbf{y}_i|\mathbf{x})d\mathbf{x} \simeq \frac{1}{M} \sum_{j=1}^M p(\mathbf{y}_i|\mathbf{x}_j)$$

where $\mathbf{x}_j \sim p(\mathbf{x})$. The entropy of \mathbf{y} is given by

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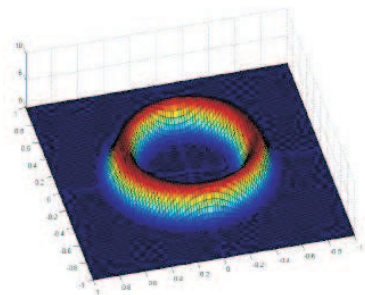
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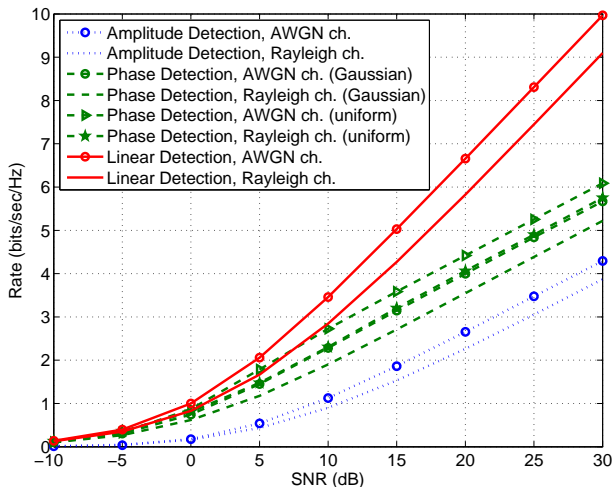
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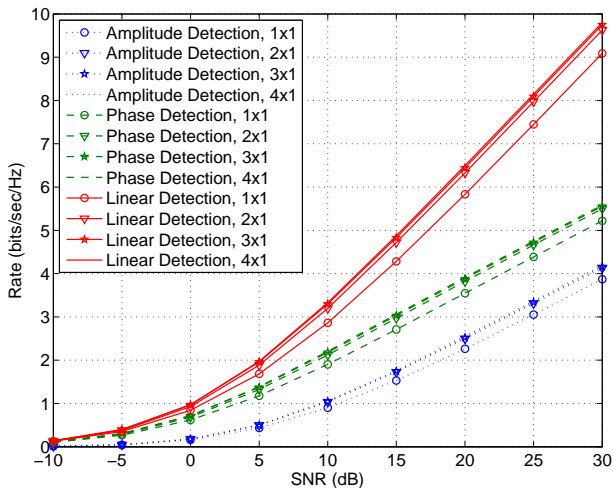
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Example: Amplitude detection, 20 dB SNR, $y = 0.5$

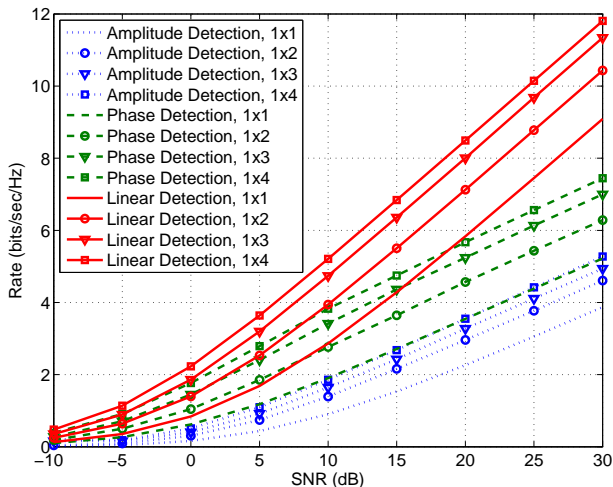


- pdf: $p(y = 0.5|x)$ for different x (x is complex valued).
- If we create samples for x Gaussian distributed, we miss the “important” area.
- Instead, we use an auxiliary function that captures the ring around $y = 0.5$.

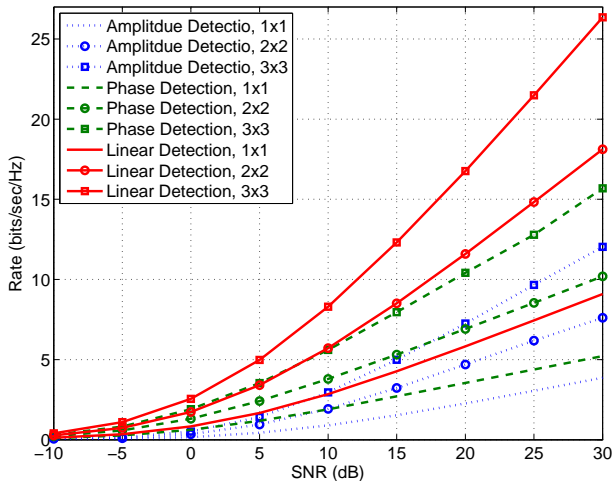




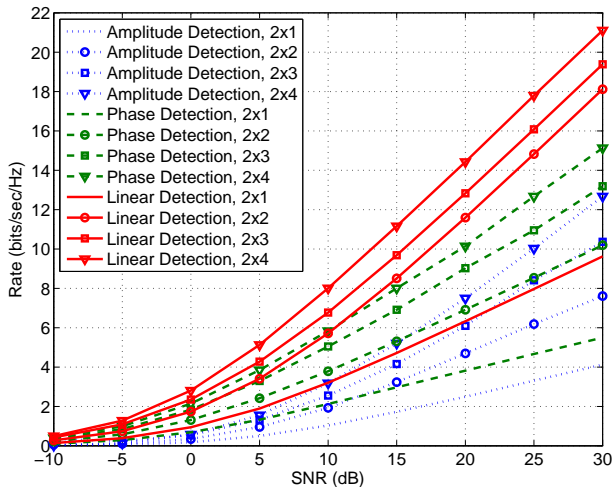
SIMO System



MIMO $N \times N$ system



MIMO $2 \times N$ system



- The performance of nonlinear receivers is clearly inferior to linear reception.
- Achievable rates of nonlinear receiver behave in a similar way as linear receivers (SIMO, MISO, etc.).
- Additional receive antennas improve the performance of nonlinear receivers (resolve more dimensions)!
- It may be cheaper to employ more nonlinear receivers than linear ones.

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Thank you for your attention!

Appendix

(M,N) MIMO	Degrees of freedom N_{\min}	Real degrees of freedom $2N_{\min}$	Slope of linear detection	Slope of nonlinear detection	Real degrees of freedom $2N_{\min} - 1$
(1,1)	1	2	2	1	1
(1,2),(2,1),...	1	2	2	1	1
(2,2)	2	4	4	2	3
(2,3)	2	4	4	~ 2.4	3
(2,4)	2	4	4	~ 2.8	3