

# Noisy Feedback Is Strictly Better Than No Feedback on the Gaussian MAC

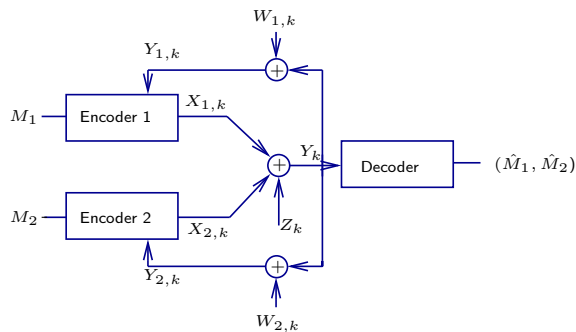
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*Thanks to Michael Gastpar and Gerhard Kramer*

# Contribution



A coding scheme achieving

- $R_{\text{sum}}(\sigma^2) > C_{\text{NoFB,sum}}$  (strictly)
- $\lim_{\sigma^2 \downarrow 0} R_{\text{sum}}(\sigma^2) = C_{\text{PFB,sum}}$

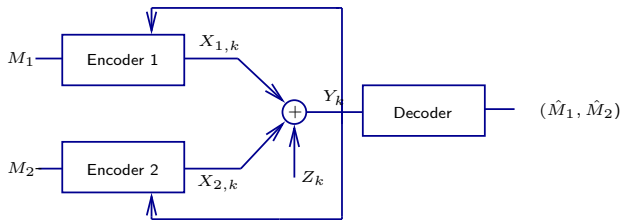
# Introduction

- Even for memoryless MACs noiseless feedback can increase capacity (Gaarder&Wolf'73)
- With noisy feedback can do at least as well as without:

$$C_{\text{NoisyFB}} \geq C_{\text{NoFB}}$$

- Can one do strictly better than without?
- We'll study the Gaussian MAC

# Perfect Feedback



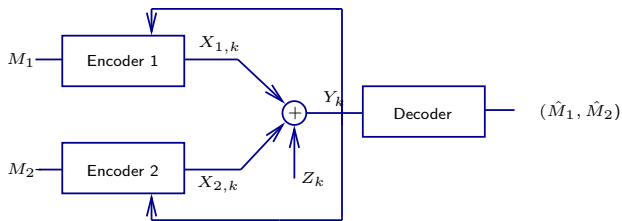
$$Y_k = x_{1,k} + x_{2,k} + Z_k$$

where  $Z_k \sim \text{IID } \mathcal{N}_{\mathbb{R}}(0, \mathcal{N})$ .

Power constraints

$$\frac{1}{n} \sum_{k=1}^n \mathbb{E} \left[ \left( x_{\nu,k}(M_{\nu}, Y_1^{k-1}) \right)^2 \right] \leq \mathcal{P} \quad \text{for users } \nu = 1, 2$$

# Perfect Feedback



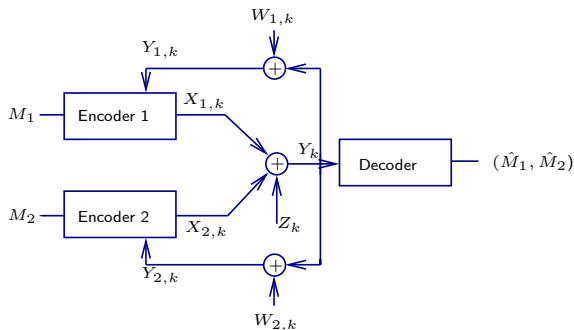
Ozarow'84:

$$C_{\text{PFB,sum}} = \frac{1}{2} \log \left( 1 + \frac{2P(1 + \rho_{Oz})}{N} \right)$$

where

$$N(N + 2P(1 + \rho_{Oz})) = (N + P(1 - \rho_{Oz}^2))^2$$

# Noisy Feedback

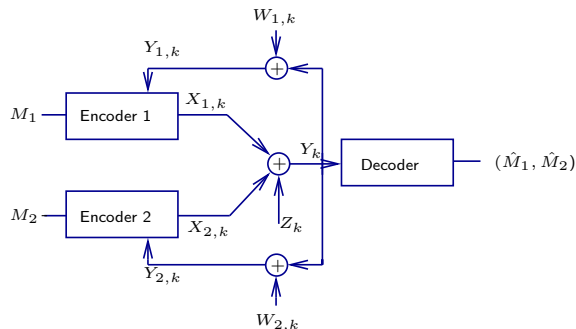


$$Y_k = x_{1,k} + x_{2,k} + Z_k \quad Y_{\nu,k} = Y_k + W_{\nu,k} \quad \nu = 1, 2$$

$$\{Z_k\} \text{ IID } \sim \mathcal{N}_{\mathbb{R}}(0, N), \quad \{W_{1,k}\} \text{ and } \{W_{2,k}\} \sim \text{IID } \mathcal{N}_{\mathbb{R}}(0, \sigma^2)$$

$$\frac{1}{n} \sum_{k=1}^n \mathbb{E} \left[ \left( x_{\nu,k}(M_{\nu}, Y_{\nu,1}^{k-1}) \right)^2 \right] \leq \mathsf{P} \quad \nu = 1, 2$$

# Noisy Feedback



- Inner bounds (Carleial'82, Willems'82, Gastpar'05)
- Strictly better than  $C_{\text{NoFB}}$  **only for  $\sigma^2$  smaller than some threshold** depending on  $(P, N)$
- Outer bound (Gastpar&Kramer'06)

# Main Result

## Theorem

*In our scheme for  $0 < P, N < \infty$*

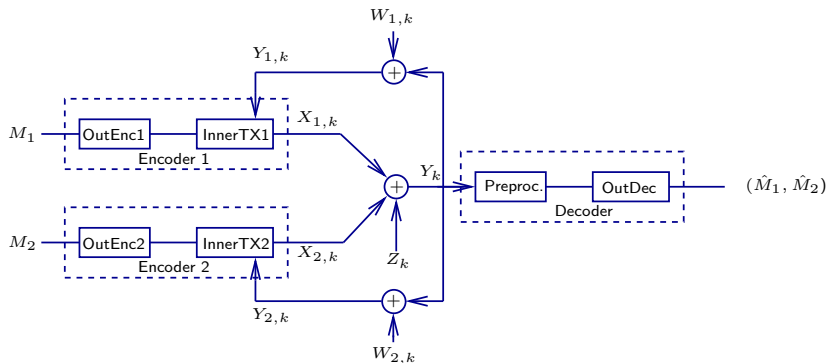
$$R_{\text{sum}}(\sigma^2) > C_{\text{NoFB,sum}} \quad \forall \sigma^2 < \infty$$

*and*

$$\lim_{\sigma^2 \downarrow 0} R_{\text{sum}}(\sigma^2) = C_{\text{PFB,sum}}$$

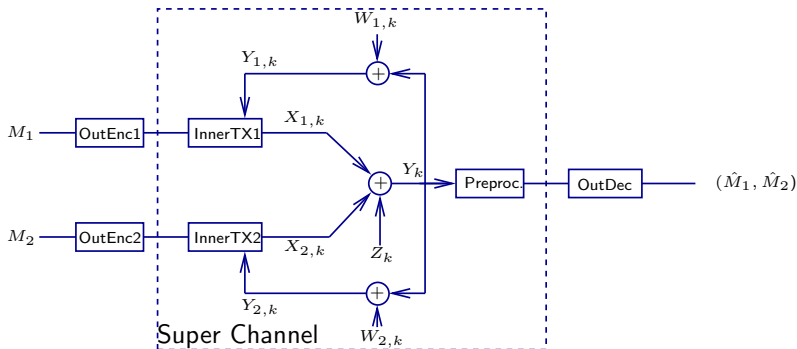


# Structure of the Concatenated Scheme



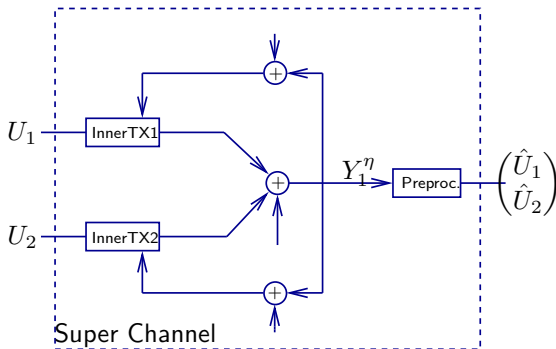
- Outer code ignores feedback
- Inner TX uses feedback

# Structure of the Concatenated Scheme



- “super channel”: inner TXs,  $\eta$  channel uses, preprocessor
- Outer Code:
  - “sees” a memoryless MAC without feedback
  - code to achieve  $C_{\text{sum}}^{(\eta)}$  (“super channel”)
- $\implies R_{\text{sum}}^{(\eta)} = \frac{1}{\eta} C_{\text{sum}}^{(\eta)}$  (“super channel”)

# Structure of the Concatenated Scheme



- “super channel”:  $\eta$  uses per single  $(U_1, U_2)$  of MAC with noisy FB
- $(\hat{U}_1, \hat{U}_2)$ : LMMSE-estimates based on  $Y_1^\eta$
- maximize  $C_{\text{sum}}^{(\eta)}$  (“super channel”), i.e.  $I(U_1, U_2; \hat{U}_1, \hat{U}_2)$

## Example for $\eta = 2$ , Inner Transmitters

- Sending  $(U_1, U_2)$
- At time 1

$$X_{1,1} = U_1$$

$$X_{2,1} = U_2$$

- with outputs

$$Y_1 = U_1 + U_2 + Z_1$$

$$Y_{\nu,1} = U_1 + U_2 + Z_1 + W_{\nu,1}, \quad \text{for } \nu = 1, 2.$$

## Example for $\eta = 2$ , Inner Transmitters

- At time 2

$$X_{1,2} = \lambda_2 (U_1 - c_1 Y_{1,1})$$

$$X_{2,2} = -\lambda_2 (U_2 - c_1 Y_{2,1})$$

where  $\lambda_2 = \sqrt{\frac{P}{(1-c_1)^2 P + c_1^2 (P+N+\sigma^2)}}$ .

- 

$$Y_2 = \lambda_2 (U_1 - U_2 - c_1 (W_{1,1} - W_{2,1})) + Z_2$$

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- Note the modulation at encoder 2!

## Example for $\eta = 2$ , Choice of $c_1$

- Maximize  $I(U_1, U_2; \hat{U}_1, \hat{U}_2)$  over  $c_1$ :

$$c_1^* = \frac{\mathbb{E}[U_1 \cdot Y_{1,1}]}{\text{Var}(Y_{1,1}) + 2\sigma^2 \frac{p}{N}} = \frac{\mathbb{E}[U_2 \cdot Y_{2,1}]}{\text{Var}(Y_{2,1}) + 2\sigma^2 \frac{p}{N}}.$$

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- Remark1: Maximizing coefficient is not LMMSE-estimation coefficient.



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- Remark1: Maximizing coefficient is not LMMSE-estimation coefficient.
- Remark2: If receiver knows  $\{W_{1,k}\}, \{W_{2,k}\}$  acausally,  $c_1^*$  is LMMSE-estimation coefficient

## Example for $\eta = 2$ , Performance

$$\begin{aligned} R_{\text{sum}}^{(2)}(\sigma^2) &= \frac{1}{2} \log \left( 1 + \frac{2P}{N} \right) + \frac{1}{4} \log \left( 1 + \frac{2P^2}{(2P + N) \left( P + N + \sigma^2 + \frac{2P}{N} \sigma^2 \right)} \right) \end{aligned}$$

$$R_{\text{sum}}^{(2)}(\sigma^2) > C_{\text{NoFB,sum}} \quad \forall \sigma^2$$

# Inner TXs, general $\eta$

Inner Transmitters:

- Sending  $(U_1, U_2)$
- At time  $k$  where  $k \in \{1, \dots, \eta\}$ :

$$X_{1,k} = \lambda_k \left( U_1 - \sum_{i=1}^{k-1} c_i Y_{1,i} \right)$$

$$X_{2,k} = (-1)^{k-1} \lambda_k \left( U_2 - \sum_{i=1}^{k-1} (-1)^{i-1} c_i Y_{2,i} \right)$$

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- Modulate the second input by  $+1$  or  $-1$ .
- Modified version of Ozarow's encoding scheme.

# Choice of $\eta(\sigma^2)$ and Convergence for $\sigma^2 \downarrow 0$

- $R_{\text{sum}}(\sigma^2)$ : Choose  $\eta(\sigma^2)$  decreasing for increasing  $\sigma^2$
- Choose  $\eta(\sigma^2)$  to be the better of  $\eta = 2$  or something exceeding

$$\sup_{\eta \geq 2} \left( R_{\text{sum}}^{(\eta)}(\sigma^2) \right) - \sigma^2$$

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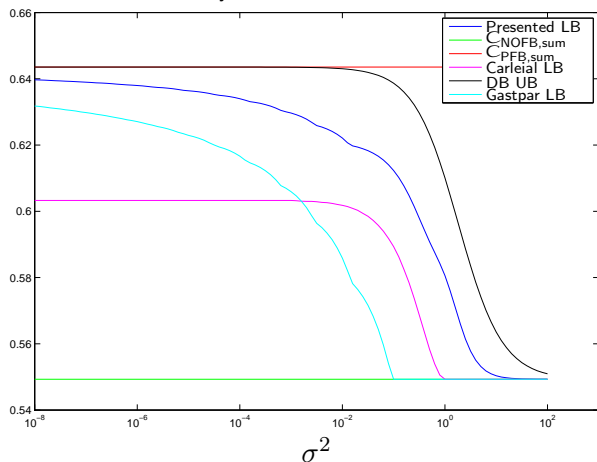
$$\sup_{\eta \geq 2} \left( R_{\text{sum}}^{(\eta)}(\sigma^2) \right) - \sigma^2$$

So that

$$\lim_{\sigma^2 \downarrow 0} R_{\text{sum}}^{(\eta(\sigma^2))}(\sigma^2) = C_{\text{PFB,sum}}$$

# Comparison to other known bounds on the Sum-Capacity

Bounds on  $C_{\text{NoisyFB,sum}}$  in nats for  $P = 1$ ,  $N = 1$



# Summary

In our scheme for  $0 < P, N < \infty$

$$R_{\text{sum}}(\sigma^2) > C_{\text{NoFB,sum}} \quad \forall \sigma^2 < \infty$$

and

$$\lim_{\sigma^2 \downarrow 0} R_{\text{sum}}(\sigma^2) = C_{\text{PFB,sum}}$$