

An introduction to Information Theory

Adrish Banerjee

Department of Electrical Engineering
Indian Institute of Technology Kanpur
Kanpur, Uttar Pradesh
India

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Lecture #12B: Parallel Gaussian Channel



Outline of the lecture

- Parallel Gaussian channel



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- Parallel Gaussian channel
- Channels with colored Gaussian noise



Parallel Gaussian channels

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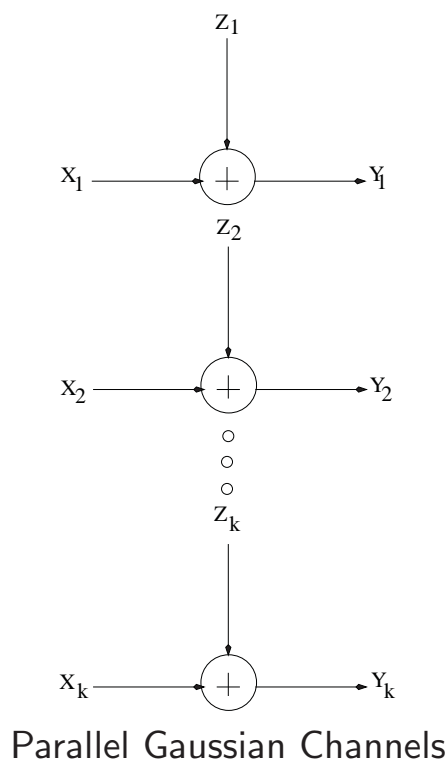
with $Z_j \sim N(0, N_j)$ and independent from channel to channel.

- Interested in distributing the power among various channels so as to maximize the total channel capacity.
- The capacity is given by

$$C = \max_{f(x_1, x_2, \dots, x_k): \sum EX_i^2 \leq P} I(X_1, X_2, \dots, X_k; Y_1, Y_2, \dots, Y_k)$$



Parallel Gaussian channels



Parallel Gaussian channels

- Since Z_i 's are independent

$$\begin{aligned} & I(X_1, X_2, \dots, X_k; Y_1, Y_2, \dots, Y_k) \\ &= h(Y_1, Y_2, \dots, Y_k) - h(Y_1, Y_2, \dots, Y_k | X_1, X_2, \dots, X_k) \\ &= h(Y_1, Y_2, \dots, Y_k) - h(Z_1, Z_2, \dots, Z_k | X_1, X_2, \dots, X_k) \\ &= h(Y_1, Y_2, \dots, Y_k) - h(Z_1, Z_2, \dots, Z_k) \\ &= h(Y_1, Y_2, \dots, Y_k) - \sum_i h(Z_i) \\ &\leq \sum_i (h(Y_i) - h(Z_i)) \\ &\leq \sum_i \frac{1}{2} \log \left(1 + \frac{P_i}{N_i} \right) \end{aligned}$$

where $P_i = EX_i^2$ and $\sum P_i = P$.

Parallel Gaussian channels

- Equality is achieved by

$$(X_1, X_2, \dots, X_k) \sim N \left(0, \begin{bmatrix} P_1 & 0 & \dots & 0 \\ 0 & P_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & P_k \end{bmatrix} \right)$$



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- The problem of optimum power allocation reduces to finding the power allocation that maximizes capacity subject to the constraint that $\sum P_i = P$.
- This can be solved using Lagrange multiplier method. The Lagrangian can be written as

$$J(P_1, \dots, P_k) = \sum \frac{1}{2} \log \left(1 + \frac{P_i}{N_i} \right) + \lambda \left(\sum P_i \right)$$



Parallel Gaussian channels

- Differentiating with respect to P_i , we get

$$\frac{1}{2} \frac{1}{P_i + N_i} + \lambda = 0$$

or

$$P_i = \nu - N_i$$



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- Since P_i must be non-negative, we have the optimal power allocation as

$$P_i = (\nu - N_i)^+$$

where ν is chosen such that

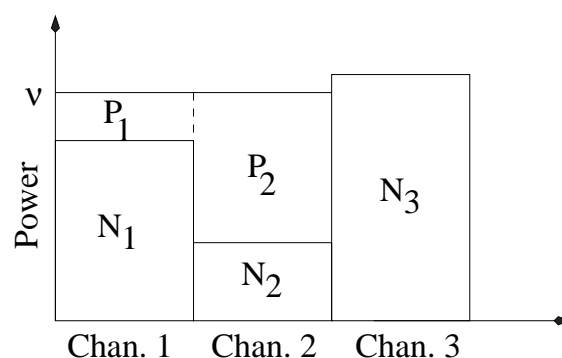
$$\sum (\nu - N_i)^+ = P$$

where

$$(x)^+ = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$



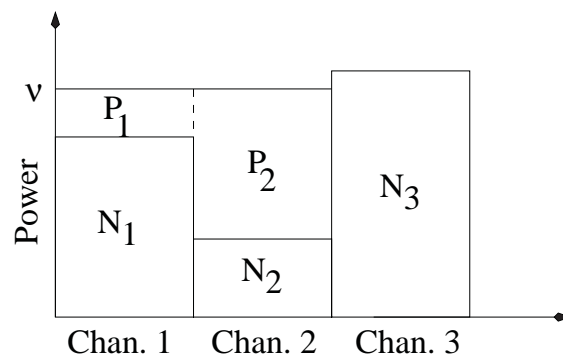
Parallel Gaussian channels



- Vertical level indicates noise levels in various parallel channels.



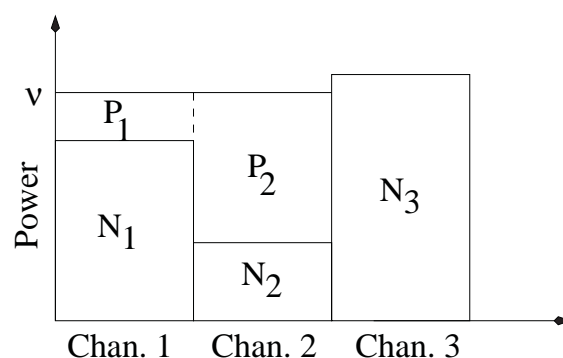
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- As power is increased from zero, we start allocating power to the channels with lowest noise.
- This process of power allocation among various channels is identical to water distributing itself in a vessel, hence this is known as “waterfilling” method.



Channels With Colored Gaussian Noise

- Let K_Z be the covariance matrix of the noise, and let K_X be the input covariance matrix. The power constraint on the input can then be written as

$$\frac{1}{n} \sum_i EX_i^2 \leq P$$

or equivalently,

$$\frac{1}{n} \text{tr}(K_X) \leq P$$



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- Here $h(Z_1, Z_2, \dots, Z_n)$ is determined only by the distribution of the noise and is not dependent on the choice of input distribution.



Channels With Colored Gaussian Noise

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- The entropy of the output is maximized when Y is normal, which is achieved when the input is normal.
- Since the input and the noise are independent, the covariance of the output Y is $K_Y = K_X + K_Z$ and the entropy is

$$h(Y_1, Y_2, \dots, Y_n) = \frac{1}{2} \log((2\pi e)^n |K_X + K_Z|)$$



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- Now the problem is reduced to choosing K_X so as to maximize $|K_X + K_Z|$, subject to a trace constraint on K_X .



Channels With Colored Gaussian Noise

- To do this, we decompose K_Z into its diagonal form,

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- Then

$$\begin{aligned} |K_X + K_Z| &= |K_X + Q\Lambda Q^t| \\ &= |Q||Q^t K_X Q + \Lambda||Q^t| \\ &= |Q^t K_X Q + \Lambda| \\ &= |A + \Lambda| \end{aligned}$$

where $A = Q^t K_X Q$



Channels With Colored Gaussian Noise

- Since for any matrices B and C ,

$$\text{tr}(BC) = \text{tr}(CB)$$

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- Now the problem is reduced to maximizing $|A + \Lambda|$ subject to a trace constraint $\text{tr}(A) \leq nP$.



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- We apply Hadamard's inequality which states that the determinant of any positive definite matrix K is less than the product of its diagonal elements, that is,

$$|K| \leq \prod_i K_{ii}$$

with equality iff the matrix is diagonal.



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- Thus,

$$|A + \Lambda| \leq \prod_i (A_{ii} + \lambda_i)$$

with equality iff A is diagonal.



Channels With Colored Gaussian Noise

- Since A is subject to a trace constraint,

$$\frac{1}{n} \sum_i A_{ii} \leq P$$

and $A_{ii} \geq 0$, the maximum value of $\prod_i (A_{ii} + \lambda_i)$ is attained when

$$A_{ii} + \lambda_i = \nu$$



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- However, given the constraints, it may not always be possible to satisfy this equation with positive A_{ii} . In such cases, we can show by the standard KuhnTucker conditions that the optimum solution corresponds to setting

$$A_{ii}(\nu - \lambda_i)^+,$$

where the water level ν is chosen so that $\sum A_{ii} = nP$.



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- This value of A maximizes the entropy of Y and hence the mutual information.

