

Lecture 5: Reliable Communications

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Outline

- Energy efficiency reliable communication via Orthogonal Codes
- Rate efficient reliable communication via Linear Block Codes
- Basic Coding Theory

Recap Last time, we introduced repetition code which has vanishing error probability. At the price of:

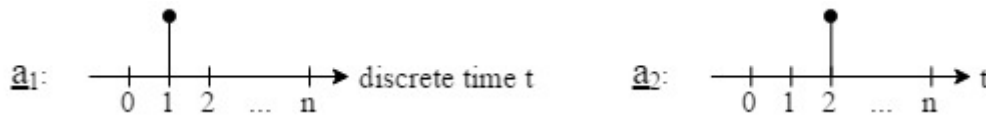
1. Vanishing Rate (Rate $\rightarrow 0$ as $n \rightarrow \infty$)
2. Unbounded energy per bit ($E_b \rightarrow \infty$ as $n \rightarrow \infty$)

Obviously, we can do better because repetition code is too simple minded.

1 Energy Efficient Reliable Communication

1.1 Orthogonal Codes

Select n orthogonal vectors in \mathbb{R}^n and use this n vectors $\{\underline{a}_1, \underline{a}_2, \dots, \underline{a}_n\}$ as the constellation set. When the noise is iid Gaussian, WLOG we can choose $\underline{a}_i = \underline{e}_i \sqrt{E_s}$ where \underline{e}_i is the i^{th} standard basis (because rotation doesn't effect the performance of the code)



Rate: $R = \frac{\log_2 n}{n}$ (bits/symbol time) $\rightarrow 0$ as $n \rightarrow \infty$

Energy per bit: $E_b = \frac{E_s}{\log_2 n}$

1.2 Probability of error (SER)

Because we have the same error event for $i = 1 \sim n$,

$$\begin{aligned}
 P_e^{(n)} &= Pr\{\hat{i} \neq 1 \mid i = 1\} \text{ (i is the selected index of the pulse)} \\
 &= Pr\left\{\bigcup_{j=2}^n \{\hat{i} = j\} \mid i = 1\right\} \\
 &\leq \sum_{j=2}^n Pr\{\hat{i} = j \mid i = 1\} \text{ (union bound, can be improved)} \\
 &= \sum_{j=2}^n \mathbb{P}_2\{1 \rightarrow j\} \text{ (binary detection that misclassify } \underline{a}_1 \text{ to } \underline{a}_j) \\
 &= \sum_{j=2}^n Q\left(\frac{\|\underline{a}_1 - \underline{a}_j\|}{2\sigma}\right) \\
 &= (n-1) \cdot Q\left(\frac{\sqrt{2E_s}}{2\sigma}\right) \\
 &= (n-1) \cdot Q\left(\sqrt{\frac{E_s}{2\sigma^2}}\right)
 \end{aligned}$$

$$\begin{aligned} &\leq (n - 1) \exp\left(-\frac{1}{4} \cdot \frac{E_s}{\sigma^2}\right) \\ &\leq n \cdot \exp\left(-\frac{1}{4} \cdot \frac{E_s}{\sigma^2}\right) \\ &\leq \exp\left(\ln n - \frac{1}{4} \cdot \frac{E_s}{\sigma^2}\right) \end{aligned}$$

Now we hope to find the relationship between n and E_s to have R.C.

$$\ln n < \frac{1}{4} \frac{E_s}{\sigma^2} = \frac{1}{4\sigma^2} E_b \cdot \log_2 n \Leftrightarrow \frac{E_b}{\sigma^2} > 4 \frac{\ln n}{\log_2 n} = 4 \ln 2$$

$$\therefore \text{Energy per bit } E_b = \frac{E_s}{\log_2 n} > (4 \ln 2) \sigma^2$$

Question: Is $4 \ln 2$ the best constant?

Answer: No, using a smarter argument (tighter bound than union bound), we can show that the constant is $2 \ln 2$ for orthogonal code.

Using Shannon's channel coding theorem, we can find that the constant $2 \ln 2$ is optimal for this problem.

1.3 Shannon's Capacity Formula

$$C = \frac{1}{2} \log\left(1 + \frac{P}{\sigma^2}\right), P : \text{power}$$

If $R < C$, then there exist a code with rate R s.t. $P_e^{(n)} \rightarrow 0$ as $n \rightarrow \infty$ (R.C. is possible)

If $R > C$, then for all coding schemes with rate R , $P_e^{(n)} \rightarrow 1$ as $n \rightarrow \infty$ (R.C. is impossible)

We can use this result to compute the optimal rate efficiency and energy efficiency:

- Optimal Rate: $C = \frac{1}{2} \log_2\left(1 + \frac{P}{\sigma^2}\right)$

- Optimal (minimum) energy per bit:

$$R < \frac{1}{2} \log_2\left(1 + \frac{P}{\sigma^2}\right) \Rightarrow 1 + \frac{P}{\sigma^2} > 2^{2R} \Rightarrow P > (2^{2R} - 1) \sigma^2$$

$$\text{energy per bit} = \frac{P(\text{energy per symbol time})}{R(\text{bits per symbol time})} = E_b(\text{energy per bit})$$

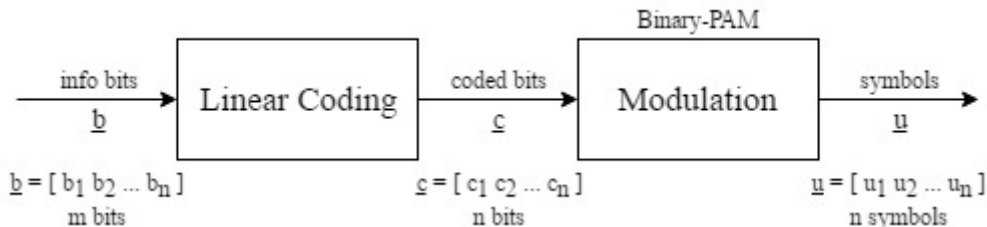
$$\Rightarrow E_b = \frac{P}{R} = \frac{1}{R} (2^{2R} - 1) \cdot \sigma^2$$

$$\min E_b = \lim_{R \rightarrow 0} \frac{1}{R} (2^{2R} - 1) \sigma^2 = 2 \ln 2 \cdot \sigma^2$$

2 Rate Efficient Reliable Communication

2.1 Linear Block Code

We use a simple architecture:



$$\therefore \text{Rate } R = \frac{m}{n}$$

For encoding, we use Linear Block Code: $\underline{c} = \underline{b} \cdot G$, $G \in \{0, 1\}^{m \times n}$, matrix with $\{0, 1\}$ entries (arithmetic in Binary Field $\mathbb{F}_2 = \{0, 1\}$)

For decoding, we use maximum likelihood (ML) rule

$$\underline{y} = \underline{u} + \underline{z}, \text{ ML decoding: } \underline{y} \rightarrow \boxed{\text{ML}} \rightarrow \underline{z}, \text{ likelihood function: } Pr\{\underline{y} | \underline{b}\}$$

Below we show that "most" linear codes guarantees arbitrarily low pe with $R > 0$

The goal here is not constructing a explicit linear transformation G , we show the existence of G instead.

2.2 Probability of error analysis

How to pick G ? Total number of possible G is 2^{mn}

Step1: randomly choose G

$(G)_{ij} \stackrel{\text{iid.}}{\sim} \text{Ber}(\frac{1}{2}), \forall (i, j) \in [m] \times [n]$

Step2: Compute the average-over-random- G performance

Consider a particular realization of $\mathbb{G}, G, \varepsilon$: error event

Probability of error when the codebook is G : $Pr\{\varepsilon | \mathbb{G} = G\}$

Let's compute the expected Prob. of error over random \mathbb{G} :

$$\begin{aligned} \mathbb{E}_{\mathbb{G}}[Pr\{\varepsilon | \mathbb{G}\}] &= \sum_{G \in \{0,1\}^{m \times n}} \left(\frac{1}{2}\right)^{mn} Pr\{\varepsilon | \mathbb{G} = G\} \\ &= \left(\frac{1}{2}\right)^{mn} \sum_{G \in \mathbb{F}_2^{m \times n}} \left\{ \sum_{k=1}^{2^m} \frac{1}{2^m} Pr\{\varepsilon | \mathbb{G} = G, \underline{B} = \underline{b}_k\} \right\} \text{(seperating the cases for different } \underline{b}_k) \end{aligned}$$

Noticed that

$$\begin{aligned} Pr\{\varepsilon | \mathbb{G} = G, \underline{B} = \underline{b}_k\} &= Pr\left\{ \bigcup_{j \neq k} \{\hat{\underline{B}} = \underline{b}_j | \underline{B} = \underline{b}_k, \mathbb{G} = G\} \right\} \\ &\leq \sum_{j \neq k} Pr\{\hat{\underline{B}} = \underline{b}_j | \underline{B} = \underline{b}_k, \mathbb{G} = G\} \text{ (union bound)} \\ &= \sum_{j \neq k} \mathbb{P}_2\{\underline{b}_k \rightarrow \underline{b}_j | \mathbb{G} = G\} \\ &= \sum_{j \neq k} Q\left(\frac{\|\underline{u}_k - \underline{u}_j\|}{2\sigma}\right) \\ &= \sum_{j \neq k} Q\left(\frac{\sqrt{d(\underline{c}_k, \underline{c}_j) \cdot (2A)^2}}{2\sigma}\right) \text{ (} d(\underline{c}_k, \underline{c}_j) \text{ is the Hamming distance between } \underline{c}_k \text{ and } \underline{c}_j) \quad (1) \\ &= \sum_{j \neq k} Q\left(\frac{\sqrt{d(\underline{c}_k, \underline{c}_j)}}{\sigma} A\right) \end{aligned}$$

Therefore,

$$\begin{aligned} \mathbb{E}_{\mathbb{G}}[Pr\{\varepsilon | \mathbb{G}\}] &\leq \left(\frac{1}{2}\right)^{mn} \left(\frac{1}{2}\right)^m \sum_{G \in \mathbb{F}_2^{m \times n}} \sum_{k=1}^{2^m} \sum_{j \neq k} Q\left(\frac{A}{\sigma} \sqrt{d(\underline{c}_k, \underline{c}_j)}\right) \text{ (implies } \mathbb{G} = G) \\ &= \left(\frac{1}{2}\right)^m \sum_{k=1}^{2^m} \sum_{j \neq k} \left\{ \frac{1}{2^{mn}} \sum_{G \in \mathbb{F}_2^{m \times n}} Q\left(\frac{A}{\sigma} \sqrt{d(\underline{c}_k, \underline{c}_j)}\right) \right\} \quad (2) \end{aligned}$$

$$= \left(\frac{1}{2}\right)^m \sum_{k=1}^{2^m} \sum_{j \neq k} \left\{ \sum_{d=1}^n f(d) Q\left(\frac{A\sqrt{d}}{\sigma}\right) \right\} \quad (3)$$

$f(d)$ is the fraction of codebooks such that $d(\underline{c}_j, \underline{c}_k) = d$ ($\therefore f(d) = \binom{n}{d} \left(\frac{1}{2}\right)^n$), so

$$\begin{aligned} \mathbb{E}_{\mathbb{G}}[Pr\{\varepsilon | \mathbb{G}\}] &= \left(\frac{1}{2}\right)^m \sum_{k=1}^{2^m} \sum_{j \neq k} \sum_{d=1}^n \left(\frac{1}{2}\right)^n \binom{n}{d} Q\left(\frac{A\sqrt{d}}{\sigma}\right) \\ &\leq \left(\frac{1}{2}\right)^m \sum_{k=1}^{2^m} \sum_{j \neq k} \left(\left(\frac{1}{2}\right)^n \sum_{d=1}^n \binom{n}{d} e^{-\frac{1}{2} \frac{A^2}{\sigma^2} d} \right) \\ &\leq \left(\frac{1}{2}\right)^m \left(\frac{1}{2}\right)^n \sum_{k=1}^{2^m} \sum_{j \neq k} (1 + e^{-\frac{1}{2} \frac{A^2}{\sigma^2}})^n \quad (4) \\ &\leq \left(\frac{1}{2}\right)^m \left(\frac{1}{2}\right)^n 2^m \cdot 2^m (1 + e^{-\frac{1}{2} \frac{A^2}{\sigma^2}})^n \end{aligned}$$

$$\begin{aligned}
 &= \left(\frac{1}{2}\right)^{n-m} \left(1 + e^{-\frac{1}{2} \frac{A^2}{\sigma^2}}\right)^n \\
 &= 2^n \left(\log_2(1 + e^{-\frac{1}{2} \frac{A^2}{\sigma^2}}) - 1 + R\right)
 \end{aligned}$$

A sufficient condition for $E_G[Pr\{\varepsilon | G = G\}] \rightarrow 0$ as $n \rightarrow \infty$ is :

$$\begin{aligned}
 &R - 1 + \log_2(1 + e^{-\frac{1}{2} \frac{A^2}{\sigma^2}}) < 0 \\
 \Leftrightarrow &R < 1 - \log_2(1 + e^{-\frac{1}{2} \frac{A^2}{\sigma^2}}) \text{ (assume } = R^*) \\
 &R^* > 0 \Rightarrow R^* \in (0, 1)
 \end{aligned}$$

(1) is because \underline{u}_i is the modulated symbol (Binary-PAM here) of coded bits \underline{c}_i , so $\underline{u}_i \in \{A, -A\}$

(2) is by changing the order of summation

You can obtain (3) by separating the cases of different $d(\underline{c}_k, \underline{c}_j)$ in the curly brackets in (2)

(4) is due to the Binomial theorem, we add the $d = 0$ term in it so it's an inequality

2.3 Conclusion

When we choose G randomly, we show that "on-average" $P_e \rightarrow 0$ as $n \rightarrow \infty$ as long as $R < R^*$

So when $R < R^*$, there must exist a particular G s.t. $P_e \rightarrow 0$ as $n \rightarrow \infty$

Now we find a coding scheme that satisfy:

1. Rate efficient: any $R < R^*$ is OK

2. Energy efficient: $E_b = \frac{A^2}{R^*}$ finite $\Rightarrow E_b \geq \lim_{A \rightarrow 0} \frac{A^2}{1 - \log_2(1 + \exp(-\frac{1}{2} \frac{A^2}{\sigma^2}))} = (4 \ln 2) \sigma^2$

3 Hard Decision v.s. Soft Decision

So far, we see that linear block codes combined with very simple modulation(binary - PAM) is able to attain rate efficient and energy efficient reliable communication.

But issues are :

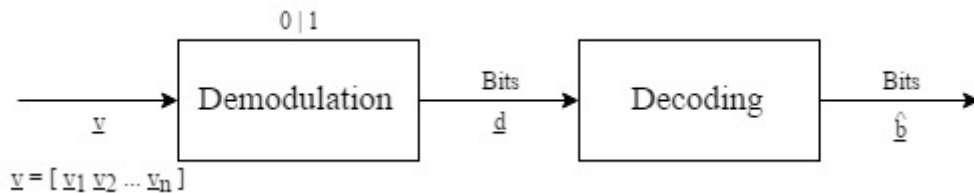
1. No explicit construction for G

2. Use ML rule for decoding is too costly in complexity($\Theta(e^n)$)

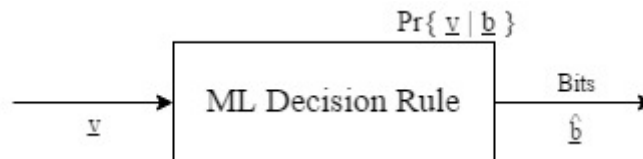
Actually, we need to have "structured" encoding and codebook so that low-complexity decoding is possible.

Can we do better if we first convert the received code symbols back to group of bits?

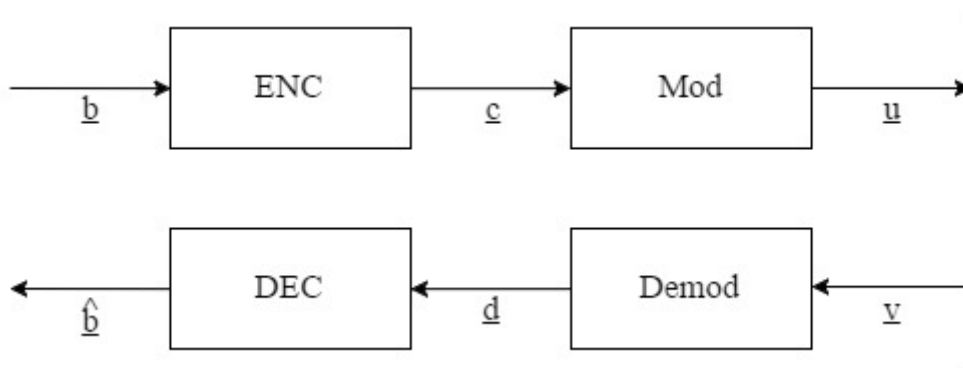
Hard Decision:



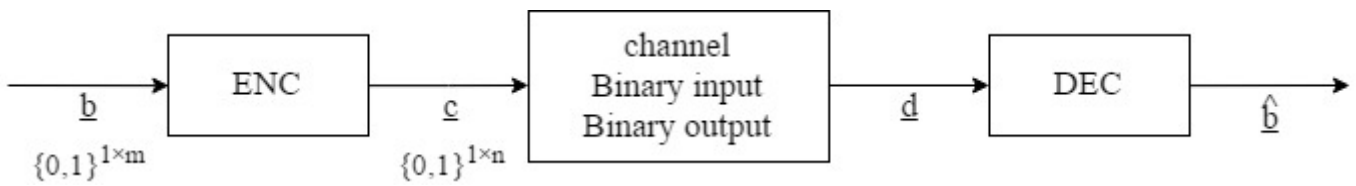
Soft Decision:



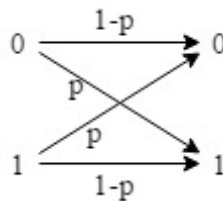
Recall the channel coding diagram:



Here is a equivalent channel:



In Lab 2, we have to characterize the end-to-end bit error rate p of this black box:



ML decoding under hard decision

Likelihood function:

$$Pr\{d|\underline{c}\} = (1 - p)^{n-d(\underline{c},d)} p^{d_H(\underline{c},d)} = (1 - p)^n \left(\frac{p}{1 - p}\right)^{d_H(\underline{c},d)}$$

ML rule:

$$\hat{c} = \arg \max_{\underline{c} \in C} \left(\frac{p}{1 - p}\right)^{d_H(\underline{c},d)} = \arg \min_{\underline{c} \in C} d_H(\underline{c}, d)$$

Still, the decoding complexity is exponential.