

WELCOME TO EE379A !! Data Transmission Design 2024 Winter Quarter

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Lecture 1 Discrete Message Encoding/Decoding January 9, 2024

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Announcements & Agenda

Announcements

- **People Introductions**
- Web site **EE379A** (see also canvas)
- Chapters 1-8 on-line at this class web site (Course Reader)
- Sections 1.1 and 1.2 today
- See last/backup slide today for matlab toolboxes I use
- Qualcomm and/or Samsung internships (send me email)
 - Apple, Intel, Ericsson

Today

- Course introduction
- Discrete Data Transmission & Examples (1.1)
- Modulation and Demodulation (1.2)
- Detection(1.1.2) ٠
- Vector Channels (1.1.1) •
 - Detection and Decision Regions (1.1.3) ٠



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Welcome Course Info Course Reader Lectures Handouts Homework Matlab Additional Topics

Winter Ouarter 2023-2024

EE 379A - Data Transmission Design





•	Problem Set 1 = PS1 due Wednesday Jan 17 at 17:00		
	1. 1.1	a constellation	
	2. 1.2	inner products	
	3. 1.3	same constellation, different modulators	
	4. 1.7	Irrelevancy and decision regions	
	5. 1.10	constellation invariances	



Intro: Why Communications?

This fundamental area is always needed. Many decades: it surges at times

If you love it, it is absolutely great area to enjoy working for your decades ahead.

Next Generation Connectivity



Digital Twins used to forecast/emulate each



Beam "me" there, Scotty







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Defense ("5/6G.mil") Clothing, Computing, ...

Samsung: 6G "hyper connected"

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L1:5

Broadband Internet Access (\$1.5T/year)



Metaverse - VR/AR focus and Bandwidth

VR and AR require efficient increase in wireless capacity





International Mobile Telecommunications (IMT)







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L1: 8

Communications Depth Sequence



- Modulation and Coding compliment one another
 - Modulation = energy assignment to time/frequency/space, is separate from:
 - Coding = distinct message mapping.
 - If both done well, they separate.



Basic Communication (digital)





Chapter 1 Intro

3 Basic Problems to Solve

• CHANNEL IDENTIFICATION - what is $p_{y/x}$?

• CODING & MODULATION - What are good (best) x and p_x for a given channel?

DETECTION – What is a good (best) receiver for deciding which x ?



Chapter 1 Intro

L1: 11

Discrete Data Transmission & Examples

Section 1.1.1

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Discrete Message Transmission



Channel \in {fiber, copper, wireless, disk/SSD, flesh, qubit, ... }

- Designers identify a channel's vector conditional-probability description $p_{y/x}$.
 - This allows a common design framework across different channel types/models.
- m_i , one of $M < \infty$ discrete messages (a vector "symbol" x), is sent every symbol period of T seconds.
 - Messages are represented by symbol vectors, 1-to-1 mapping from messages.
 - Later $m_i \rightarrow m$.
 - $b = \log_2(M) =$ number of bits (in message).
- Conversion to/from actual (often continuous-time "analog") is "modulation,"
 - and left unspecified in this general discrete-message-transmission model.
 - Many different modulation methods can conform to the same discrete message-transmission system.



Section 1.1.1

Transmitted-Symbol Quantities

Name	Definition
$M = 2^b \in \mathbb{Z}^+$	number of messages , corresponding to $b \ge 0$ information bits
$T \in \mathbb{R}$	symbol period; $1/T$ is the symbol rate
$R = \frac{b}{T} \in \mathbb{R}$	data rate.
$egin{array}{c} x \end{array}$	transmitted symbol value (typically a real or complex vector)
$C \subset \mathbb{R}^N$	constellation that consists of all possible symbol values $\{x_i \mid i = 0, \mid C \mid -1\}$
	with $ C \ge M$ and in this chapter, always equal.
$p_m(i) \in \mathbb{R}$	message's probability distribution, $i = 0,, M - 1$
$p_{\boldsymbol{x}}(i) \in \mathbb{R}$	symbol value's probability distribution $= p_m(i)$
$N \in Z^+$	number of real temporal dimensions per transmit symbol
	the receive symbol has $N + \nu$ dimensions with default $\nu = 0$ and $\nu \in \mathbb{Z}$
$L_x \in \mathbb{Z}^+$	number of transmit spatial dimensions
$L_y \in \mathbb{Z}^+$	number of receive spatial dimensions

Table 1.1: Table of transmitted-symbol quantities' definitions.



dB (decibels) are measured as $10 \cdot \log_{10} energy \text{ or power}$ = $20 \cdot \log_{10} amplitude$ often relative to 1 mW (dBm)

L1: 14

Example 1: Light-Pulse Bit Transmission



- If $T = 10 \ ps$, then $R = 100 \ \text{Gbps} \ (10^{11}) \ \text{bits/second}$.
- $x \in \{0, X_{max}\}.$
- "non-coherent" or "direct-detection" optical transmission.



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Section 1.1.1.1

L1: 15

Example 2: Wireless



- Channel adds noise and has multiple paths that can align positively or negatively.
- Discrete modulator $x = A \cdot e^{j\theta}$ (64 complex vectors, one for each message); while $y = H \cdot x + n$.
- $1/_T = 100 MHz$, so R = 600 Mbps.



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Section 1.1.1.1

L1: 16

4 megapixel photograph



- Number of dimensions $N = 2280 \times 1640 \times 3$ (exactly 11,217,600).
- M = 8; b = 3.
- R = 3 bits/photo, where T = 1 photo.

Today's machine-learned facial ID reduces to this basic system, with perhaps large *M*



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Section 1.1.1.1

L1: 17

distance measurement (radar, lidar)



Modulation and Demodulation

(a foundation: Sections 1.1-1.2)

See PS1.1 and PS1.2

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Conversion to continuous-time ("analog")



- Modulator converts the symbol vector x to a continuous-time signal x(t).
- Demodulator reverses continuous time channel output y(t) to the vector y.
- Detector decides which symbol decision \hat{x} minimizes the error probability that $\hat{x} \neq x$.



Section 1.2

Example BPSK (wireless revisited)



- Simple ±1 inputs are not good for this channel, why?
- The modulator tries to match the signal vector to the channel;
 - while the discrete optical-pulse channel appears similar, it has a different modulator.
- However, designers may apply the same analysis to both, as we'll see.



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Section 1.2

L1: 21

Formal Modulation – math model



- The basis functions match what the channel can pass well (in good designs).
- Symbol vector has a scalar component x_n for each dimension (one basis function/dimension, so N dimensions).

The constellation $C = \{x_1, x_2, ..., x_M\}$ (note set of *boldface* vectors, one for each message).

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Section 1.2.1

L1:22

 $\varphi_1(t)$

Binary Phase-Shift Keying (BPSK) and Manchester Examples

• **BPSK** with T = 100ms (10 bits/second):

$$\varphi_1(t) = \sqrt{\frac{2}{T}} \cdot \cos\left(\frac{2\pi t}{T} + \frac{\pi}{4}\right) \quad 0 \le t \le T$$
$$\varphi_2(t) = \sqrt{\frac{2}{T}} \cdot \cos\left(\frac{2\pi t}{T} - \frac{\pi}{4}\right) \quad 0 \le t \le T$$

• Manchester Code with T = 100ms (10 bits/second) is better for simple channels with "binary" transmission:





Analysis will be same, but modulators differ (because symbols x_0 and x_1 are the same).



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PS1.3 (1.3)

Section 1.2.2

L1: 23

Common Constellations

 $\frac{1}{1+1} \varphi_1(t)$

 $\varphi_2(t)$

+1

 x_0

 \boldsymbol{x}_1

Common constellation:



• Other Examples:



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Demodulator



Section 1.2.4

BPSK matched-filter demodulator

The BPSK modulator from slide 22 has corresponding matched-filter demodulator:



- The matched filter's convolution with original basis function produces unity norm at time *T*.
- The convolution is perfectly matched to maximize signal energy output at sampling time *T*.
- No other (unit-norm) filter sampled at any time can produce a larger SNR (see section 1.3.1.3 proof).



Section 1.2.4

L1:26

Inner Products

Definition 1.2.2 [Inner Product] The inner product of two (real) functions of time u(t) and v(t) is

$$\langle u(t), v(t) \rangle \stackrel{\Delta}{=} \int_{-\infty}^{\infty} u(t) \cdot v(t) dt$$
 (1.41)

The inner product of two (real) vectors \boldsymbol{u} and \boldsymbol{v} is



$$(1.41)$$
$$u(t) = \sum_{n=1}^{N} u_n \cdot \varphi_n(t)$$
$$v(t) = \sum_{n=1}^{N} v_n \cdot \varphi_n(t)$$
$$(1.42)$$

where * denotes vector transpose (and conjugate vector transpose later when complex signals are introduced). $\|u\|^2 = \langle u, u \rangle$

Easy to prove that

$$\langle u(t), v(t)
angle = \langle oldsymbol{u}, oldsymbol{v}
angle$$

And further that

Theorem 1.2.2 [Parseval's Identity] The following relation holds true for any modulated waveform

$$\mathcal{E}_{\boldsymbol{x}} = \mathbb{E}\left[||\boldsymbol{x}||^2\right] = \mathbb{E}\left[\int_{-\infty}^{\infty} x^2(t)dt\right] \quad . \tag{1.48}$$



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PS1.2 (1.2)

Section 1.2.3

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MIMO Channels



Section 1.2.5

Optimum Detection Section 1.1.2

See PS1.3 (Prob 4.18), PS1.4 (Prob 4.7), and PS1.5 (Prob 4.25)

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Minimum Error Probability

Definition 1.1.3 [Error Probability] The Error Probability is $P_e \stackrel{\Delta}{=} P\{\hat{m} \neq m\}$. The corresponding probability of being correct is therefore $P_c = 1 - P_e = 1 - P\{\hat{m} \neq m\} = P\{\hat{m} = m\}$.

• maximum \dot{a} posteriori (MAP) detector – given some observed channel output y = v is $p_{x/y}$.

$$P_{c}(\hat{m} = m_{i}, \boldsymbol{y} = \boldsymbol{v}) = p_{m/\boldsymbol{y}}(m_{i}, \boldsymbol{v}) \cdot p_{\boldsymbol{y}}(\boldsymbol{v}) = \underbrace{p_{\boldsymbol{x}/\boldsymbol{y}}(\boldsymbol{x}_{i}, \boldsymbol{v})}_{MAP} \cdot p_{\boldsymbol{y}}(\boldsymbol{v}) = \underbrace{p_{\boldsymbol{y}/\boldsymbol{x}}(\boldsymbol{x}_{i}, \boldsymbol{v})}_{ML} \cdot p_{\boldsymbol{x}_{i}}$$
Not function of \boldsymbol{x}_{i}

• If $p_{x_i} = \frac{1}{M}$, then Maximum Likelihood (ML) is $p_{y/x}$.



The MAP and ML Rules

Rule 1.1.1 [MAP Detection Rule]

$$\hat{m} \Rightarrow m_i \quad if \quad p_{\boldsymbol{y}/m}(\boldsymbol{v},i) \cdot p_m(i) \ge p_{\boldsymbol{y}/m}(\boldsymbol{v},j) \cdot p_m(j) \quad \forall \quad j \ne i$$
 (1.8)

If equality holds in (1.8), then the decision can be assigned to either message m_i or m_j without changing the minimized error probability.

Rule 1.1.2 [ML Detection Rule]

$$\hat{m} \Rightarrow m_i \quad if \quad p_{\boldsymbol{y}/m}(\boldsymbol{v}, i) \ge p_{\boldsymbol{y}/m}(\boldsymbol{v}, j) \quad \forall \quad j \ne i \quad .$$
 (1.10)

If equality holds in (1.10), then the decision can be assigned to either message m_i or m_j without changing the error probability.

Assume that all messages are equally likely, use ML (almost always).

Examples in Lecture 2 and beyond.

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If the inputs have unequal probabilities, they can be compressed to lower rate with equally likely probabilities.



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Section 1.1.2.1-2

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Decision Regions

Definition 1.1.4 [Decision Region] The decision region using a MAP detector for each message m_i , i = 0, ..., M - 1 is defined as

$$\mathcal{D}_i \stackrel{\Delta}{=} \{ \boldsymbol{v} \mid p_{\boldsymbol{y}/m}(\boldsymbol{v}, i) \cdot p_m(i) \ge p_{\boldsymbol{y}/m}(\boldsymbol{v}, j) \cdot p_m(j) \quad \forall \ j \neq i \} \quad .$$
(1.12)



• Detector "precomputes" the associated decision for every specific value of y = v.



Sec 1.1.3

Decision Regions and Error Probability

For any decision region

$$\mathbb{E}[P_c] = \sum_{i=0}^{M-1} \sum_{\boldsymbol{v} \in \mathcal{D}_i} P_c(\widehat{m} = m_i, \boldsymbol{y} = \boldsymbol{v} \in \mathcal{D}_i)$$

For MAP

$$P_{c,max} = \mathbb{E}[P_c] = \sum_{i=0}^{M-1} \left\{ \sum_{\boldsymbol{v} \in \mathcal{D}_i} P_{\boldsymbol{y}/m_i}(\boldsymbol{v}, m_i) \right\} \cdot p_{m_i}$$

$$P_{e,min} = 1 - P_{c,max}$$

These (double) sums often simplify greatly, as we'll see.





End Lecture 1

- Discrete Data Transmission & Applications
- Encoding and Detection (decoding)
- Modulation and Demodulation
- Vector Channels
- Probability (see Appendix A) happy to help, off hours, help

Cioffi uses these toolboxes

