

A \rightarrow D • quantization quantified by SQNR

- optimal quantization

- Important for Comm schemes with digital backends, analog info

What if TXing digital information?

↳ What does this really mean?

transmission always occurs in CS-time

I am trying to both transmit and receive data which is already quantized (a string of bits)

→ quantification of noise/loss is very different (^{rate of} bit errors)

→ do not care about SQNR

Basics

Tuesday, October 6, 2020 6:11 PM

Multiple binary coding schemes

"Natural Binary Code" (NBC) N levels, $0 \rightarrow N-1$

$0000 \rightarrow 0$

$0001 \rightarrow 1$

$0010 \rightarrow 2$

⋮

$1111 \rightarrow 15$

Gray Coding: Two successive values differ by only one bit.

3-bit: $0 \rightarrow 000$

$1 \rightarrow 001$

$2 \rightarrow 011$

$3 \rightarrow 010$

$4 \rightarrow 110$

$5 \rightarrow 111$

$6 \rightarrow 101$

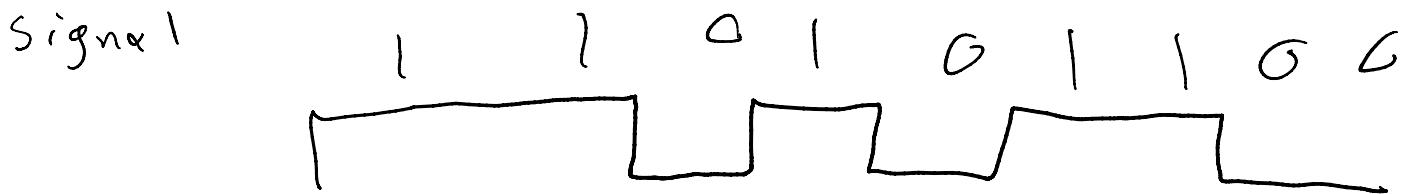
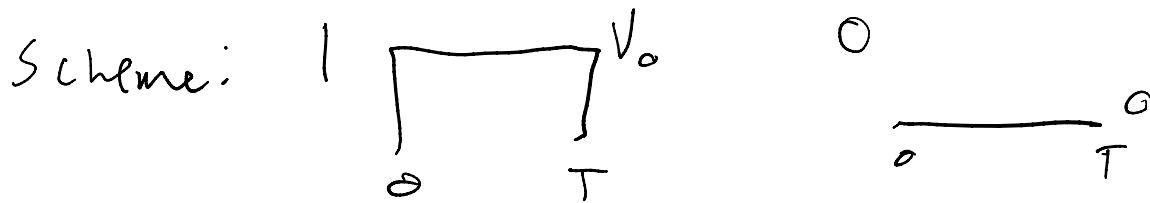
$7 \rightarrow 100$

In NBC b -bits, 2^{b-1} is the largest error I can get from 1 bit error

In Gray, 1 is the largest (mfp. of b)

Problem: I want to transmit my coded 1s and 0s
but the world is Analog!

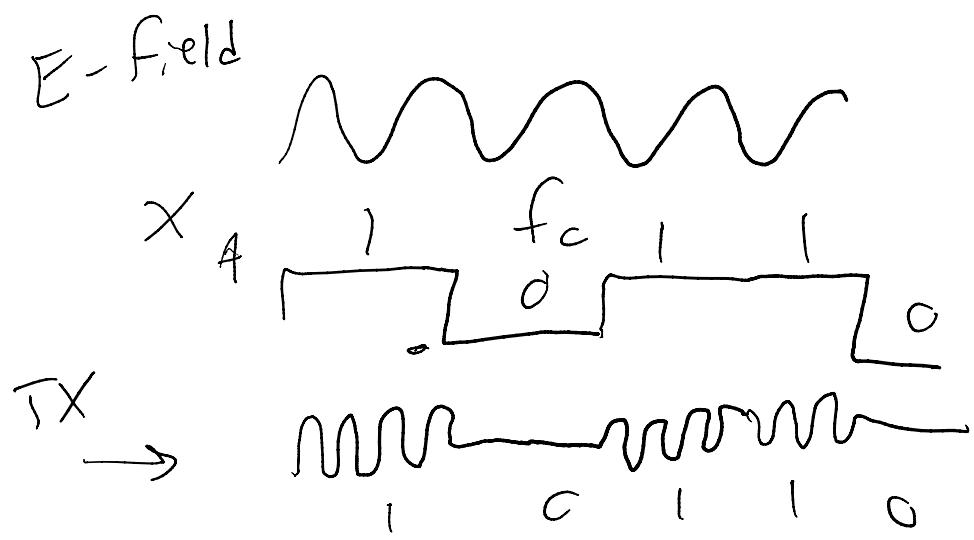
DLD Solution Channel: a wire



cts-line signal representing a digital signal.

How about via E+M waves?

Simple scheme:



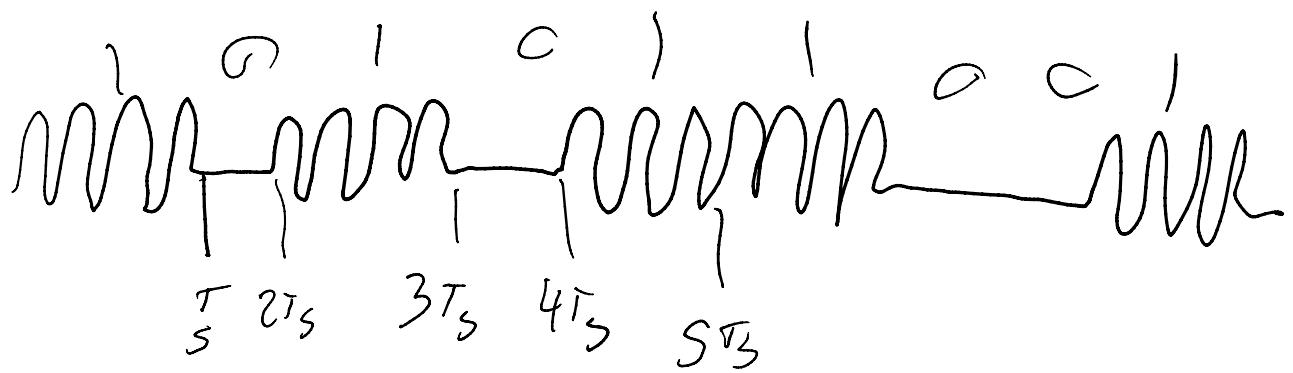
Digital data trying to send over IR

$$\lambda \sim 1100 \text{ nm}$$

$$c = 3 \times 10^8 \text{ m/s} \quad f \approx 270 \text{ THz}$$

On-off keying (OOK)

envelope which is 0 over intervals of length T_s represent 0s, A over intervals of length T_s rep. 1s



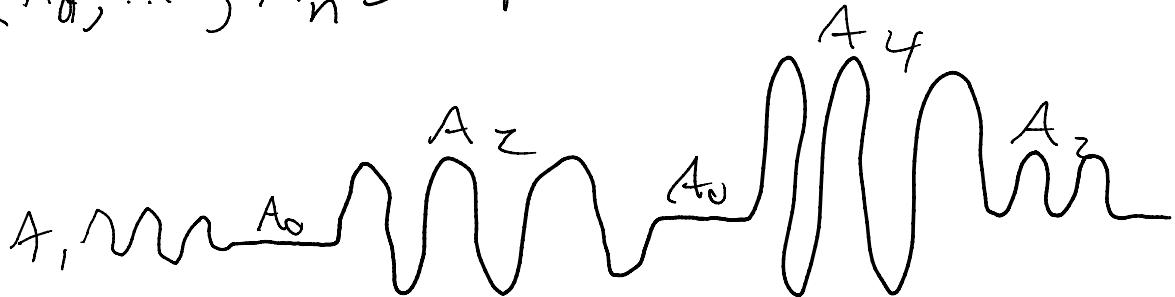
On-off keying - very natural, useful when TX mechanism has very high freq.

You only need the incoming Power as a function of time
✓ phase info not needed - rate 1 bit/ T_s

Amplitude Shift keying

Generalization of OOK with multiple levels

Generalization of OOK with multiple levels
 $\{A_0, \dots, A_n\}$ represent ^{different} b.i.t - sequences



each A_i level (and thus each pulse of T_S duration) can represent $\log_2(n+1)$ bits

$$\text{rate } \log_2(n+1) \text{ bits}/T_S$$

If I want to represent X values, how many bits do I need?

$$A: \log_2 X$$

$$\underbrace{\quad}_{b_0} \underbrace{\quad}_{b_1} \dots \underbrace{\quad}_{b_{N-1}}$$

2^N values with N bits e.g. 8 bits $\rightarrow 0 \rightarrow 255$

N values rep. by $\log_2 N$ bits

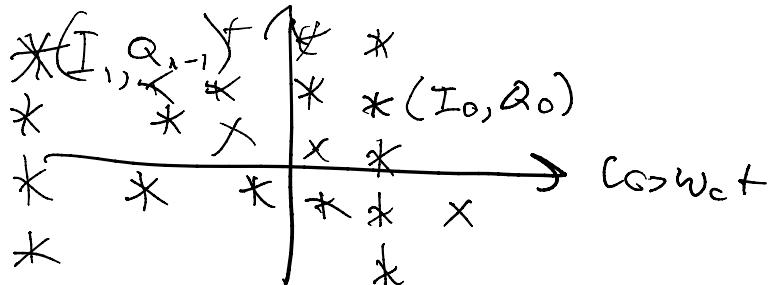
$$\log_2 X \text{ bits rep. } 2^{\log_2 X} \text{ values} = X \text{ values}$$

RF transmission, where I send

$$I_i \cos \omega_c t - Q_j \sin \omega_c t$$

$$\{I_0, \dots, I_{n-1}\}, \quad \{Q_0, \dots, Q_{m-1}\}$$

as phasors, these look like $\begin{pmatrix} \sin \omega_c t \\ \cos \omega_c t \end{pmatrix}$



↑
Constellation,

$$\text{Signal } I_i \cos \omega_c t - Q_j \sin \omega_c t$$

distinct from others only if both amp and phase taken into account

$n \cdot m$ possible (I, Q) pairs

Each signal in const. represents $\log_2(nm)$ bit string

Constellations \rightarrow many comm schemes

Before (AM) : Learn a new mod scheme

→ first question - how does noise impact this?

... How do we decide if we receive a certain signal?

do k case



I register incoming power of a pulse $P_r \neq 0$
 $\neq P_0$

because of noise

which signal was it?

in this case w/ 2 possibilities I might say

"received 1" if $P_r > T$, some threshold

"received 0" else

What about for ASK?

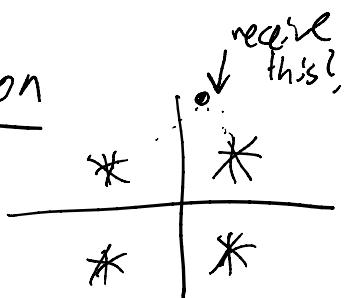
less simple - I might need N thresholds

"received A₀" if $0 \leq P_r < T_0$

"received A₁" if $T_0 \leq P_r < T_1$

etc

for constellation



etc

a natural guess is
 L^2 distance min

generally: need 2D decision regions

"received \vec{a}_i " if $r(t) \in R_i < R^2$

in all 3 cases: need to pick decision regions

Q: What are the best decision regions?

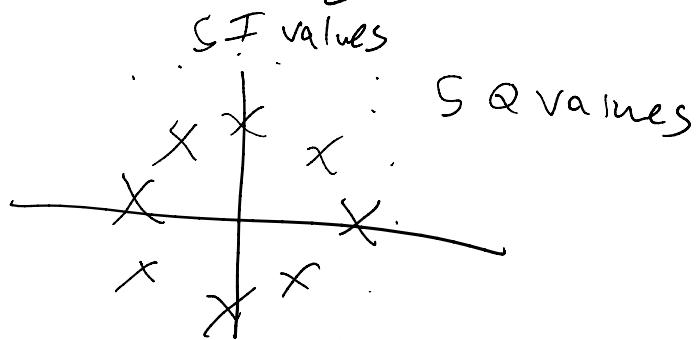
$I_c \cos\omega t - Q_j \sin\omega t$

$\{I_0, \dots, I_{n-1}\}, \{Q_0, \dots, Q_{m-1}\}$

if $\{I, Q\} = \{I_0, \dots, I_{n-1}\} \times \{Q_0, \dots, Q_{m-1}\}$

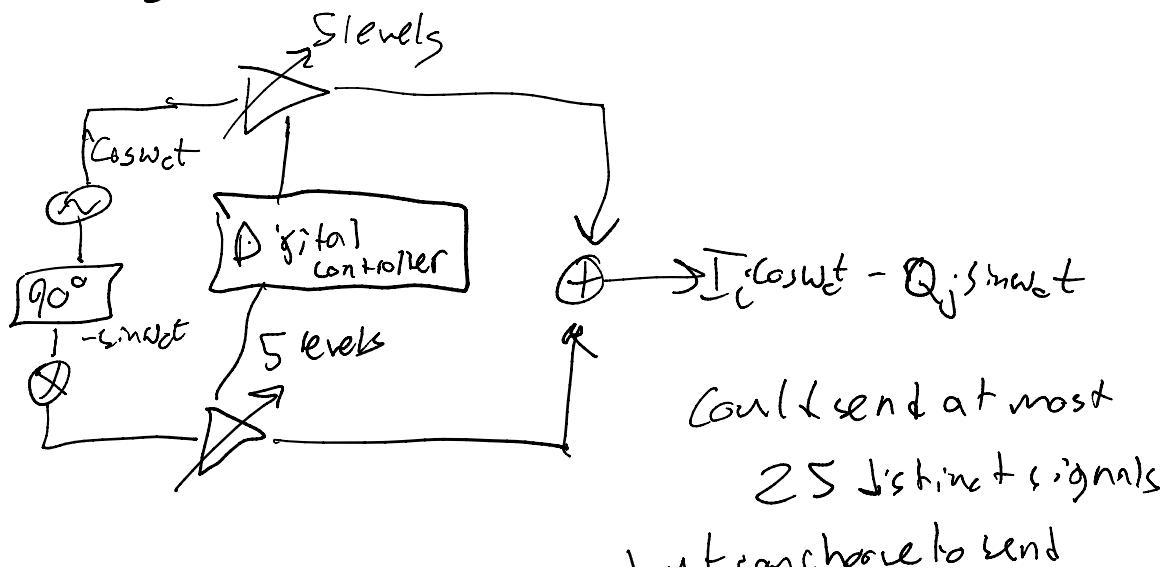
I get all ordered pairs \rightarrow rectangular const.

Can I restrict $\{I, Q\}$ to a subset of this product



but only 8 total const. points

represent fewer bit strings than a rectangle
but all signals have same 1.)



10

>> J'stinct signals
but can choose to send
fewer

Decision Theory

Tuesday, October 6, 2020 6:53 PM

Mathematical context

our signals are represented by
basis vectors

$$\text{In OOK, } s_1(t) = A \cos \omega t, 0 \leq t \leq T_c$$

$$s_0(t) = 0, 0 \leq t \leq T_c$$

lives in a 1-dimensional space

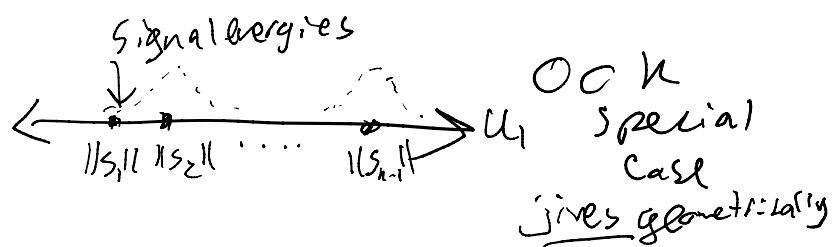
basis vector: $\frac{s_i(t)}{\|s_i(t)\|} = u_i$ e unit energy
 L^2 norm

$$s_i = 0 \cdot u_i, s_i = \|s_i\| u_i$$

$$\text{In ASK, } s_i(t) = A_i \cos \omega t, 0 \leq t \leq T_c$$

$$u_i = \frac{s_i}{\|s_i\|} \text{ for any } s_i$$

$$s_i = \|s_i\| u_i$$



'nearness' geometrically = susceptibility to noise

In constellations - same idea but 2-dim
(I, Q already define dims)

In constellations - some even use

(I, Q already define dims
already orthogonal signal
components)

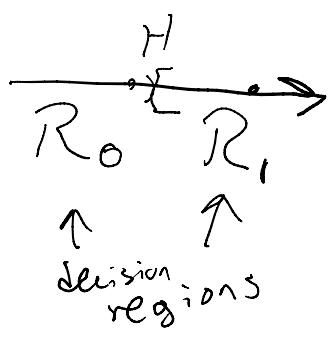
"nearness" is precisely L^2 distance

Constrain to OOK

1st Strategy to decide decision regions

minimize Prob. of a mistake

$$P[\text{mistake}] = P[\text{guess } 1 \mid I \text{ TX } 0] + \\ P[\text{guess } 0 \mid I \text{ TX } 1]$$



$$\text{receive } Y = \int_0^T |y(t)|^2 dt \in \mathbb{R}$$

Y is either \geq or $<$ H my threshold

$$P[\text{error}] = P[Y \in R_1 \mid I \text{ transmitted } 0] + P[Y \in R_0 \mid I \text{ transmitted } 1]$$

$$= \int_{R_1} f_{Y|I=0}(y) dy + \int_{R_0} f_{Y|I=1}(y) dy$$

our decision algorithm should say

$$\text{if } P[y \text{ and } \hat{x} = 0] > P[y \text{ and } \hat{x} = 1]$$

then decide 0

happens if $y \in R_0$

more generally for K classes

$$P[y \text{ and } \hat{x} = x_i] > P[y \text{ and } \hat{x} = x_j] \quad \forall j \neq i$$

max. $P[y \text{ and } \hat{x} = x_i]$ over i

$$P[y \text{ and } \hat{x} = x_i] = P[\hat{x} = x_i | y] P[y]$$

$P[y]$ is common to this term for each i ,

$$\max P[y \text{ and } \hat{x} = x_i] \Leftrightarrow \boxed{\max P[\hat{x} = x_i | y]}$$

posterior prob.

maximum a posteriori (MAP) method -

$$\text{maximize } P[\hat{x} = x_i | y]$$

$$\rightarrow \text{MAP} \quad S_{\text{MAP}} = 1.7 - 0.1 \cdot 1.7 + 1.7 \cdot 1.7$$

$$R_i^{\text{MAP}} = \{y \mid P[\hat{x} = x_i \mid y] \geq P[\hat{x} = x_j \mid y] \forall j \neq i\}$$

(\hat{x} is the ground truth, the real transmitted signal
 y is received - x corrupted by noise)

MAP is the method which minimizes the Perror

IF I know I receive a 1 only 0.005% of the time, then

$$P[\hat{x} = 0 \mid y] = \frac{P[y \mid \hat{x} = 0] P[\hat{x} = 0]}{P[\hat{x} = 1] P[y \mid \hat{x} = 1] + P[\hat{x} = 0] P[y \mid \hat{x} = 0]}$$

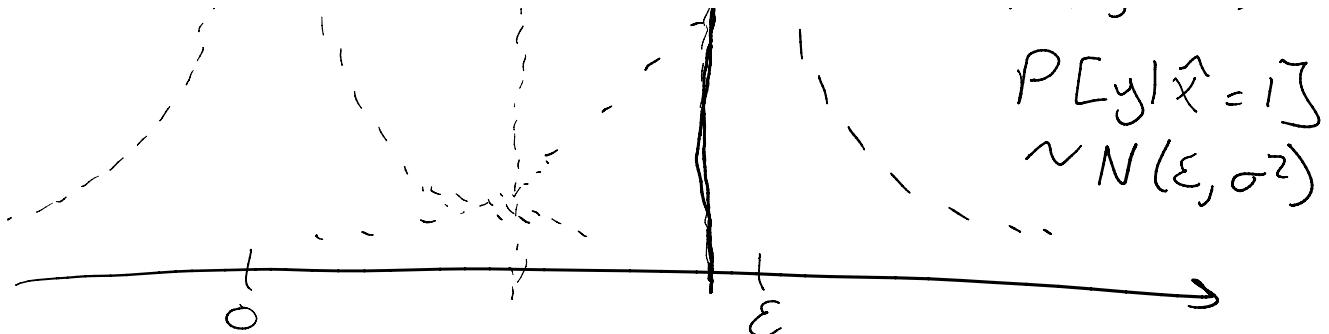
$$P[\hat{x} = 1 \mid y] = \frac{P[y \mid \hat{x} = 1] P[\hat{x} = 1]}{\text{same denom}}$$

maxing LHS is eq. to maxing $P[y \mid \hat{x} = x_i] P[\hat{x} = x_i]$

in example, $P[\hat{x} = 1]$ is very low so this will greatly affect decision region

AWGN, σ^2_{noise}

$$\begin{array}{ccc} R_0 & \dots & R_1 \\ P[y \mid \hat{x} = 0] & & \sim N(0, \sigma^2) \\ P[u \mid \hat{x} = 1] & & \end{array}$$



$$P[\hat{x}=0] \gg P[\hat{x}=1]$$

So MAP minimizes Perror but requires we know, a priori, $P[\hat{x}=x_i] \forall x_i$

Why - Bayes' THM

What if we don't know? Can't do MAP! (or, rather, we have to assume priors $P[\hat{x}=x_i]$)

Instead - we look to maximize

$$P[y | \hat{x} = x_i] \leftarrow \text{different conditional order than MAP}$$

likelihood
fnctn

Bayes' THM

$$P[\hat{x} = x_i | y] = \frac{P[y | \hat{x} = x_i] P[\hat{x} = x_i]}{\sim}$$

↑
Posterior

Call this method ML or maximum likelihood

Classification methods involve finding minimum error

$$R_i^{\text{ML}} = \left\{ y \mid P[y | \hat{x} = x_i] \geq P[\hat{x} = x_j] \forall j \neq i \right\}$$

Note: $\max P[y | \hat{x} = x_i]$ (ML)

is same as $\max P[\hat{x} = x_i | y] = \underbrace{P[y | \hat{x} = x_i]}_{\sim} P[\hat{x} = x_i]$

if $P[\hat{x} = x_i]$ is i -independent
(i.e., equiprobable events)

MAP = ML \Leftrightarrow all x_i are equiprobable

In BOK example - to determine MAP,
need $P[\hat{x} = 0]$, $P[\hat{x} = 1]$ and numerics
regarding the tail distributions of the Gaussians to
determine R_0, R_1

To determine ML = $H = \text{mid point}$.

$E_{1/2}$

ML - "intuitive guess" knowing nothing

MAP - "sophisticated derivation" knowing something

"Minimize expected loss" $L(x_i, x_j) = \text{loss of mistaking } x_i \text{ for } x_j$

\nearrow $E[L] = \sum_i \sum_j \int_{R_j} L(x_i, x_j) P[y \text{ and } \hat{x} = x_j]$

another decision method
(not used here)

use SGD to minimize this function

A special case that does matter:

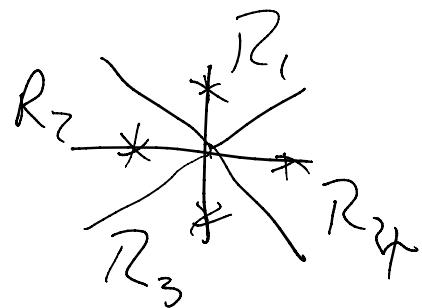
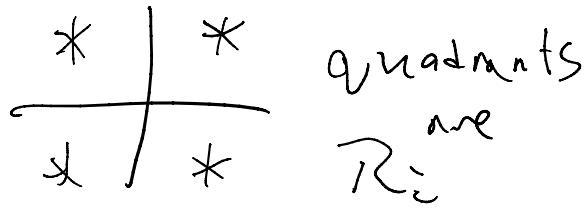
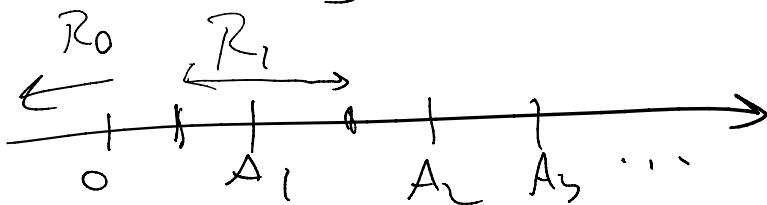
minimum square error (geometric idea)

Square error: $\|y - \hat{x}_i\|^2$

$$R_i^{\text{LSE}} = \{y \mid \|y - \hat{x}_i\|^2 \leq \|y - x_i\|^2 \forall j \neq i\}$$

no probability needed

purely geometrical



super easy method

in AWGN case,

$$M1: f = \epsilon_1$$

in AWGN case,



for AWGN, if signals are "equidistant"

* obvious

$$ML = LS$$

Stronger:

$$\boxed{AWGN \Rightarrow ML = LS}$$

$$\boxed{AWGN + \text{eqn probable} \Rightarrow ML = LS = MAP}$$

Last rule: Correlation Receiver or Matched Filter

Maximize innerproduct $\langle y, \hat{x}_i \rangle$

$$\int y(t) \hat{x}_i^*(t) dt = \langle y, \hat{x}_i \rangle \quad \begin{matrix} \leftarrow L_2 \text{ i.p.} \\ \leftarrow \text{real case} \end{matrix}$$

or more gen.

$$\max \operatorname{Re} \langle y, \hat{x}_i \rangle = \operatorname{Re} \left(\int y(t) \hat{x}_i^*(t) dt \right)$$

$$R_{\cdot}^M \Rightarrow u | R_0 \langle u, x \rangle > \operatorname{Re} \langle u, x \rangle V_i(t_i)$$

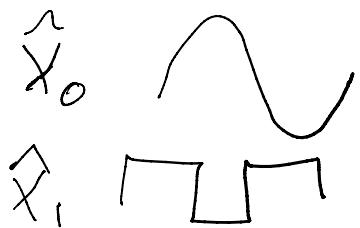
$$\mathcal{R}_i^m = \{y \mid \operatorname{Re} \langle y, x_i \rangle \geq \operatorname{Re} \langle y, x_j \rangle \forall j \neq i\}$$

$$\hat{x}_0 = \overbrace{0}^{0 \dots 0} \quad \text{num } \int 0 = 0$$

$$\hat{x}_1 = \begin{cases} 0 & 0 \dots T_s \\ A & T_s \end{cases} \quad \int A = E \geq 0 \text{ we always pick } A$$

third method

what if my scheme involved sensing different pulse shapes?

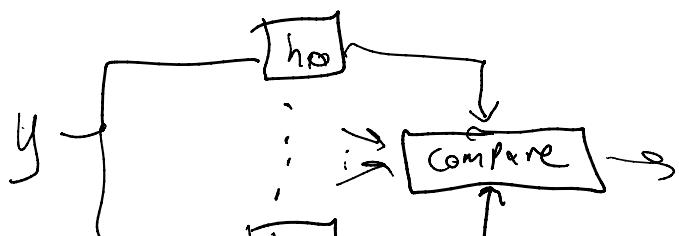


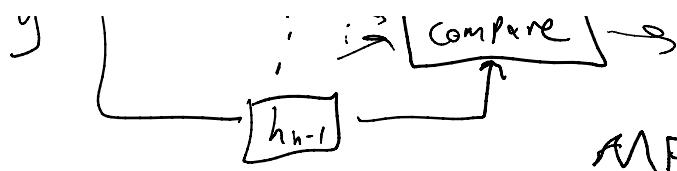
max corr. occurs if you are basically integrating the square of the signal

so long as \hat{x}_0 and \hat{x}_1 have equal energy

corr. receiver makes sense if equal energy symbols

$$h_i = \hat{x}(T_s - t) \text{ then } \langle y, \hat{x} \rangle = y + h_i$$





MF is very easy in hardware

equal energy

$$E = \int \hat{x}_i(t)^2 dt \quad \forall i$$

then

$$SE = \int (y(t) - \hat{x}_i(t))^2 dt = \underbrace{\int y^2 dt + E^2}_{i\text{-interp.}} - 2 \underbrace{\int y \hat{x} dt}_{\langle y, \hat{x} \rangle}$$

So max. MF = min. LS

Equal energy \Rightarrow MF = LS

Equal energy
+
equiprobable
+
AWGN \Rightarrow MF = LS = ML = MAP

MF = easiest hardware imp

Under these assumptions
get min. p. of error! (great :))

Binary Signaling

Tuesday, October 6, 2020 8:12 PM

Def A binary signaling scheme is one in which only

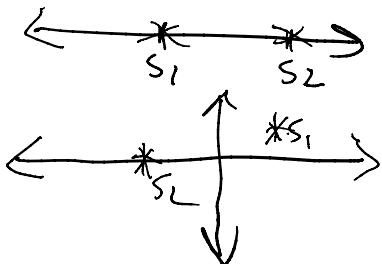
2 symbols are used, $s_1(t)$ and $s_2(t)$

→ Each symbol can represent only 1 bit of information

binary signalling schemes can live in either 1-D or
2-D

1 D case $s_1(t) = s_2(t)$

2 D case $s_1(t) \neq s_2(t)$ for any t

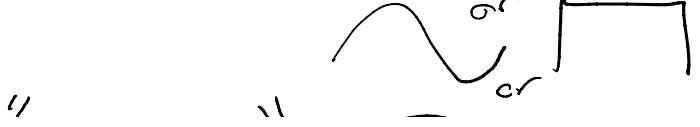


$$\frac{s_1(t)}{\|s_1(t)\|} = \psi, \text{ has unit energy, it's our first basis vector}$$

$$\int |s_1(t)|^2 dt = E \quad \text{but} \quad \|s_1(t)\| = \sqrt{\int |s_1(t)|^2 dt} = \sqrt{E}$$

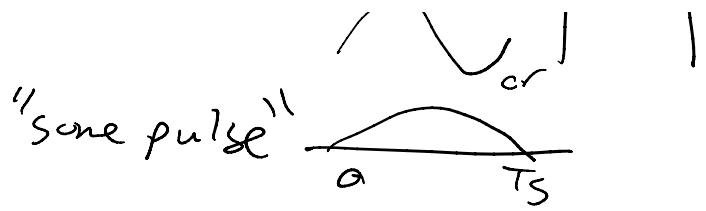
$$\psi_1 = \frac{s_1(t)}{\sqrt{E_{s_1}}}$$

Binary antipodal

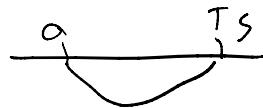


Binary antipodal

i: $s_1(t) = p(t), 0 \leq t \leq T_S$



o: $s_0(t) = -p(t), 0 \leq t \leq T_S$

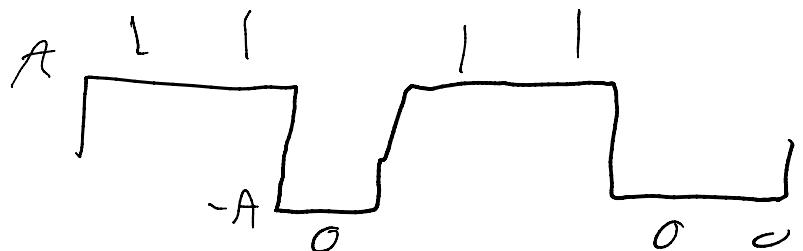


immediately clear that $E_{s_1} = E_{s_0} = \int |p(t)|^2 dt$

energy per bit $E_b = E_s / \# \text{bits rep. by } s \stackrel{\text{binary signaling}}{=} E_s$

$s_1(t) = A, 0 \leq t \leq T_B$

$s_0(t) = -A, 0 \leq t \leq T_S$



"shifted DLD" but equal energy

$$E_b = \int_0^{T_S} A^2 dt = A^2 T_S$$

"Binary Pulse Amplitude Modulation"

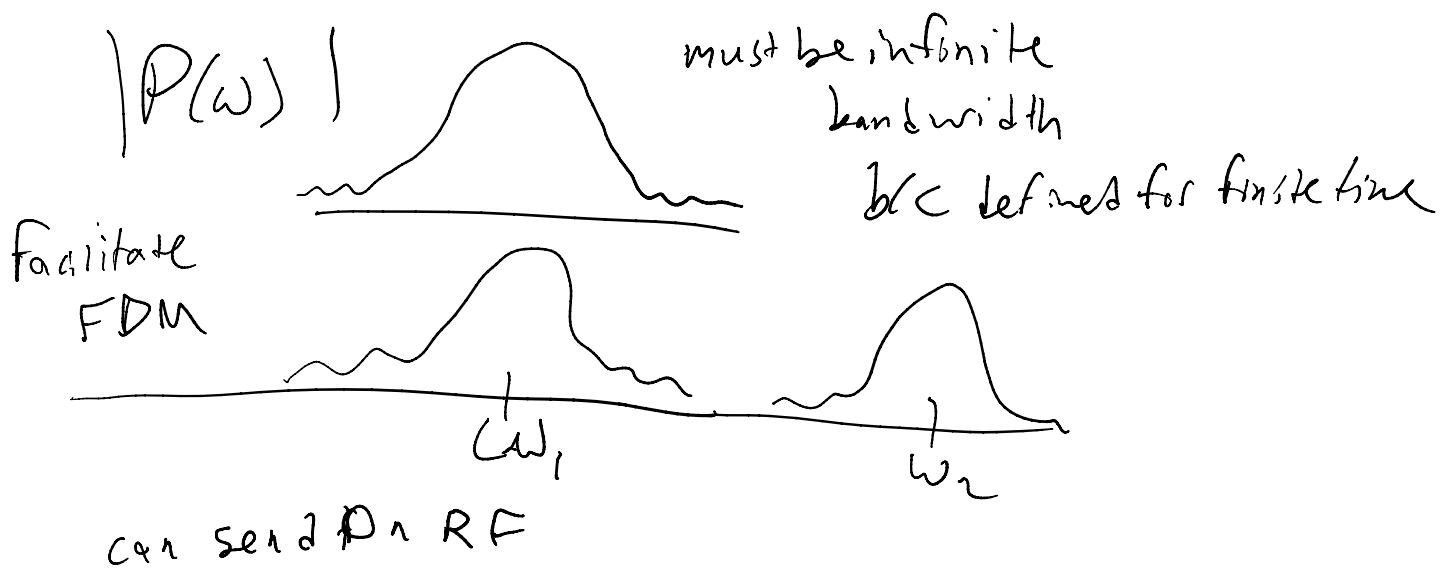
or binary PAM

$$\psi_i = \frac{s_i}{\|s_i\|} = \frac{A}{\sqrt{A^2 T_S}} = \frac{1}{\sqrt{T_S}}$$

Binary amplitude shift keying

$$S_1(t) = p(t) \cos \omega_c t \quad 0 \leq t \leq T_s$$

$$S_0(t) = -p(t) \cos \omega_c t \quad 0 \leq t \leq T_s$$

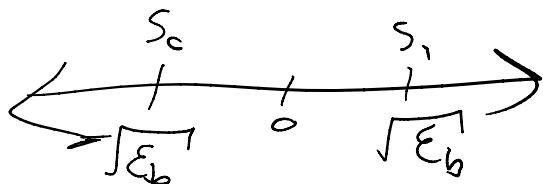


if $p(t) = A$ (rectangular)

$$S_1(t) = \sqrt{\frac{2 E_b}{T_s}} \cos \omega_c t$$

$$S_0(t) = -S_1(t)$$

$$N_1(t) = \sqrt{\frac{2}{T_s}} \cos \omega_c t, \quad 0 \leq t < T_s$$



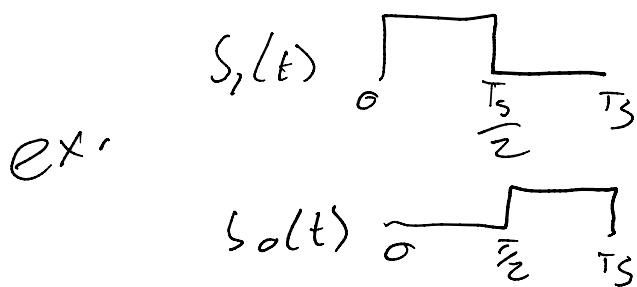
just another
antipodal
method

antipodal is the only equal energy 1-D signalling scheme

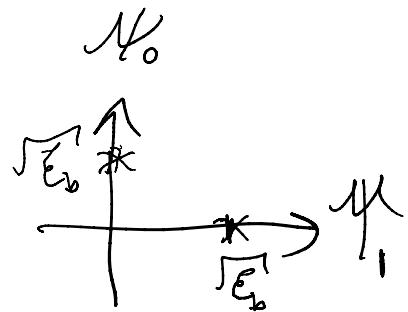
Binary signalling in 2D can be equal energy in many ways but

most common is binary orthogonal signalling

$$\begin{aligned} 1 &\rightarrow s_1(t) \\ 0 &\rightarrow s_0(t) \end{aligned} \quad \int_0^{T_s} s_1(t)s_0(t) dt = 0$$

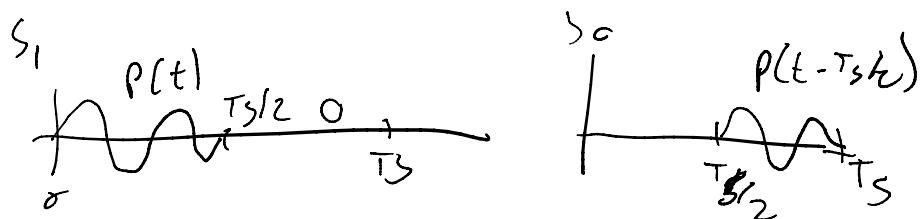


$$\psi_1 = \frac{s_1}{\|s_1\|}, \quad \psi_0 = \frac{s_0}{\|s_0\|}$$



$$s_1 = (\sqrt{E_b}, 0), \quad s_0 = (0, \sqrt{E_b}) \text{ in this basis}$$

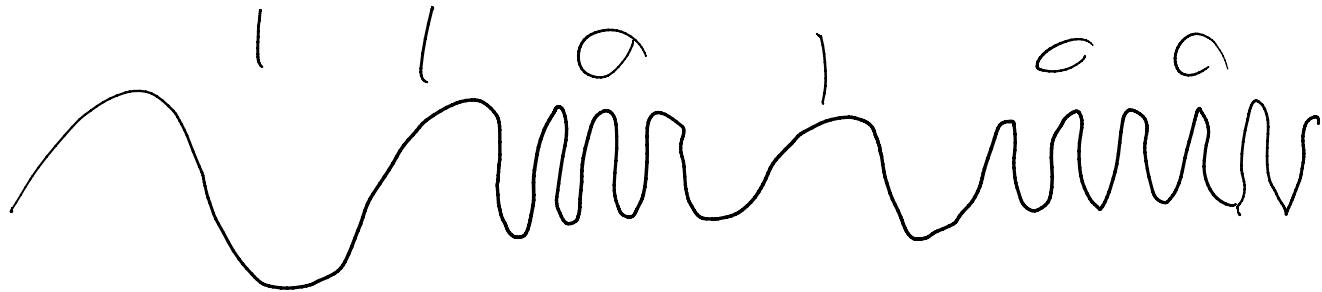
Binary pulse position modulation



Binary Frequency Shift Keying (FSK)

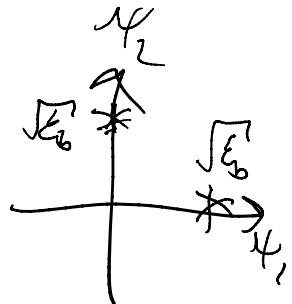
$$S_1(t) = \sqrt{\frac{2E_b}{T_s}} \cos \omega_1 t, \quad 0 \leq t \leq T_s$$

$$S_2(t) = \sqrt{\frac{2E_b}{T_s}} \cos \omega_2 t, \quad 0 \leq t \leq T_s$$



"like FM but digital"

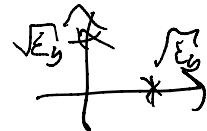
$$\psi_1 = \sqrt{\frac{2}{T_s}} \cos \omega_1 t, \quad \psi_2 = \sqrt{\frac{2}{T_s}} \cos \omega_2 t$$



Binary signaling is either 2 antipodal signals



or 2 orth. signals



AWGN

Model: $s_i(t) + n(t)$, n has PSD

$$\xrightarrow{N_0/2\sigma^2}$$

binary antipodal

$$s_0(t) = -\sqrt{E_b} \psi(t)$$

$$s_1(t) = \sqrt{E_b} \psi(t) \quad \text{for some } \psi \text{ s.t.}$$

$\psi(t) = 0$ for $t \notin (0, T_s)$
and $|\psi(t)| = 1$

$$\text{Receive } r(t) = \pm \sqrt{E_b} \psi(t) + n(t)$$

need to make decision as to whether r is s_0 or s_1
probably

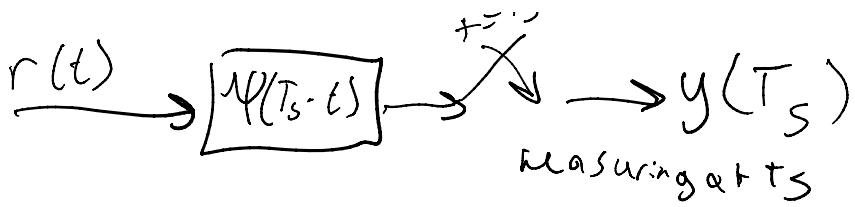
$$\begin{array}{l} \bullet \text{ AWGN} \\ \bullet \text{ Equal energy} \end{array} \left. \right\} \rightarrow MF = LS = ML$$

(if equal probable = MAP as well)

we can use MF

"integrate over T_s

$$r(t) \xrightarrow{\int_{T_{-}}^{T_{+}} |r(t)|^2 dt} u(T_{+})$$



$$y(T_s) = \int_0^{T_s} r(\tau) \Psi(\tau - T_s + T_s) d\tau$$

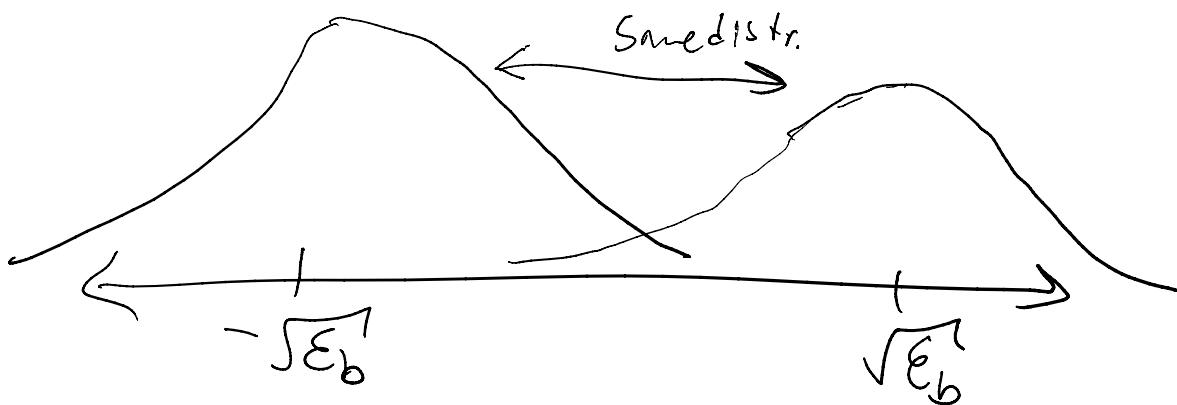
$$= \int_0^{T_s} r(\tau) \Psi(\tau) d\tau$$

$$= -\sqrt{E_b} \left(\int_0^{T_s} \Psi^2(\tau) d\tau \right)^{1/2} + \int_0^{T_s} n(t) \Psi(t) dt$$

$$= -\sqrt{E_b} + \underbrace{\int_0^{T_s} n(t) \Psi(t) dt}_{\text{filtered white noise}} \quad \begin{array}{l} \text{same mean-0} \\ \text{can show - same } \sigma^2 \\ \text{because } \|\Psi\| = 1 \end{array}$$

$$= S_i(t) + n$$

\sim distributed like $N(0, \sigma^2)$



ideal decision region in MF = LS = ML, just

Ideal decision region in $MF = LS : ML$, just
threshold at ψ
in dep. of ψ

clear that for same N_0 ,

$\nearrow E_b \quad \searrow P_{err}$ as the tail "disappears"
as you get
further from ψ