

- ↳ 4 Modules →
- 1] Converting Analog to Digital (Source Coding)
 - 2] Baseband communication
 - 3] Modulation technique & ~~coding~~ Coding

Internal Evaluation

- Surprise Quiz
- minor
- Assignment
- Project *

(10%) Hardware or Simulation for both lab & theory
4-5 slides project records

Text Book - 1. Communication System by Simon Haykin

2. Digital Communication by T. Proakis (Random process)

3. Modern Digital & analog Comm. Syst, B P Lathi

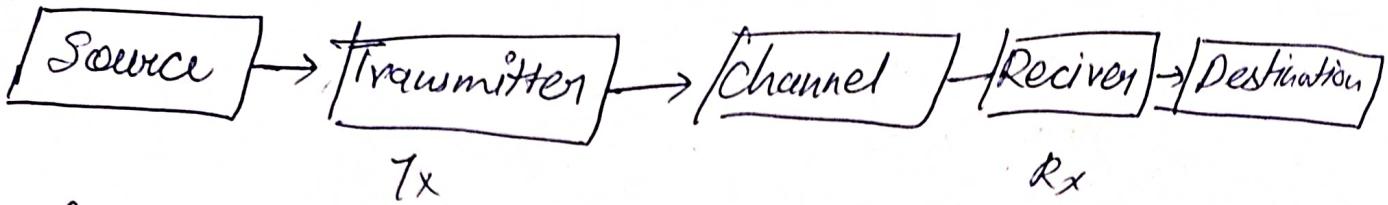
4. Digital Communication Fundamentals and Application
by Vithal B. Srivani (Exercises.)

Objectives

1. Knowledge about random Signal and their properties
2. Generalize the concept of Digital source generation.
3. Analytic knowledge on baseband and passband communication.
4. Understand the different digital modulation scheme.
5. Able to realize an efficient Digital comm. system in terms of BER and SNR
6. Basic knowledge of Coding theorem

Purpose: to transmit a signal with information to a destination

3:

Eg: fm radioTV

Source: microphone

Channel: free space

Receiver: speaker

Camera < Image
 Sen |
 microphone < video

free Space : channel

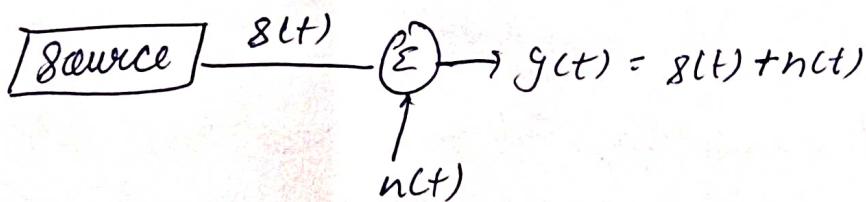
channel: wired, wireless

Randomness in channel determinist

↓
 noise < Thermal Noise
 flicker Noise

Distribution: Probability.

AWGN - Additive white Gaussian Noise

Early day's digital Communication

Telegraph

A-2

0-9
 . , , , , ? using Morse code encoded using
 short pulse (long pulse)

most frequent - short code

rare occurrence - long code

Aim - average code length
is to minimum

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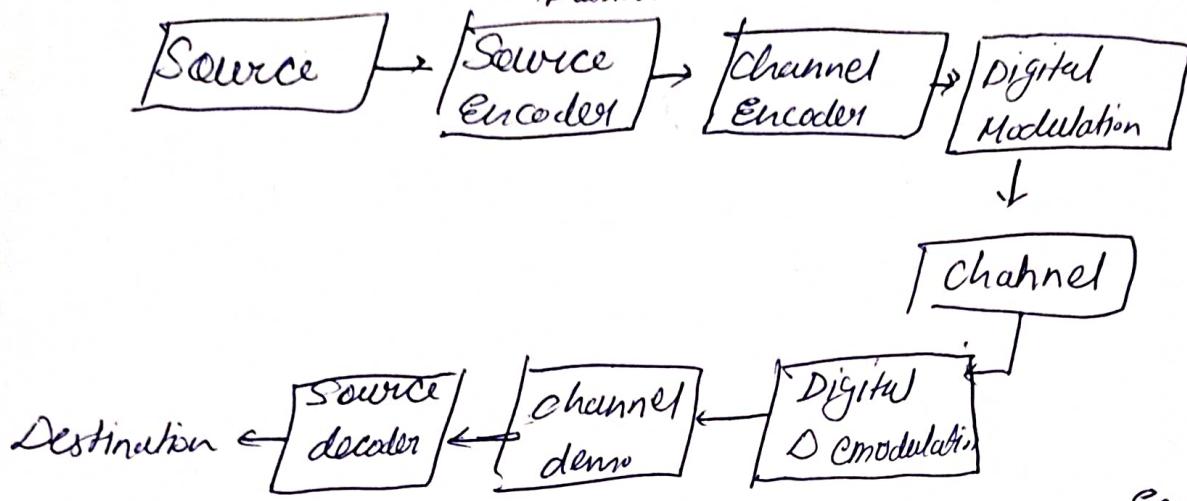
Redundancy - Remove unused information

E
 Z

$\rightarrow \cdot$
 $\rightarrow \cdot \cdot \cdot$

→ Remove the redundancy

→ compression



Error detection

→ We are adding redundancy to improve error correction/ because of channel noise

0 → 0 0 0	0 0 0 → 0
1 → 1 1 1	0 0 1 → 0
	0 1 0 → 0
	0 1 1 → 1
	1 0 0 → 0
	1 0 1 → 1
	1 1 0 → 1
	1 1 1 → 1

Probability And Random Process

Experiment * All the outcome in By throwing a dice
 ↓ a set is called
 outcome sample space $S = \{1, 2, 3, 4, 5, 6\}$

Event - Subset of Sample Space

$$S = \{1, 2, 3, 4, 5, 6\}$$

$$A_1 = \{2, 4, 6\} \quad A_2 = \{1, 2, 3\}$$

$$P(A_1) = \frac{1}{6} + \frac{1}{6} + \frac{1}{6} = \frac{1}{2}$$

$$P(A_2) = \frac{1}{2}$$

$$A = \bigcup_{i=1}^N A_i \quad P(A) \leq \sum_{i=1}^N P(A_i)$$

Exp 1

$$S = \{x_1, x_2, \dots, x_N\}$$

Exp 2

$$S = \{y_1, y_2, \dots, y_N\}$$

$P(x_i^o, y_j^o)$ \rightarrow joint probability
 \rightarrow probability of x_i^o from Exp 1 &
 probability y_j^o from Exp 2

$$\sum_{i=1}^N \sum_{j=1}^M P(x_i^o, y_j^o) = 1 \quad \int \int P(x, y) dx dy = 1$$

$$\sum_{j=1}^M P(x_i^o, y_j^o) = P(x_i^o) \quad \int p(x, y) dy = p(x)$$

\rightarrow marginal probability

$$\sum_{i=1}^N P(x_i^o, y_j^o) = P(y_j^o)$$

Conditional Probability

$P(A|B)$ = probability of A when B occurred.

$$\Rightarrow \frac{P(A, B)}{P(B)}$$

$$\begin{aligned} P(A, B) &= P(A) P(B|A) \\ &= P(B) P(A|B) \end{aligned}$$

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$$P(A, B, C) = P(A) P(B|A) P(C|A, B)$$

$$P(A_1, A_2, \dots, A_n) = P(A_1) + P(A_2|A_1) + P(A_3|A_1, A_2)$$

$$\dots + P(A_n|A_1, A_2, \dots, A_{n-1})$$

\Rightarrow If A & B are independent

$$\boxed{P(A|B) = P(A)} \quad \text{&} \quad P(A, B) = P(A)P(B)$$

Random Variable: It is mapping from sample space to real no.

$$X: S \rightarrow \mathbb{R} \quad \begin{matrix} X = \text{Random process} \\ x = \text{random variable} \end{matrix}$$

$$\{H, T\} \quad H \rightarrow -L \quad \text{or} \quad H \rightarrow 0 \\ T \rightarrow L \quad T \rightarrow L$$

Continuous Random Variable

When the image of sample space is continuous then the rand. variable is called conti -续 random variable

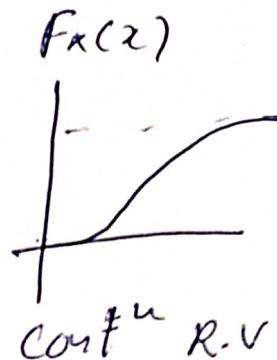
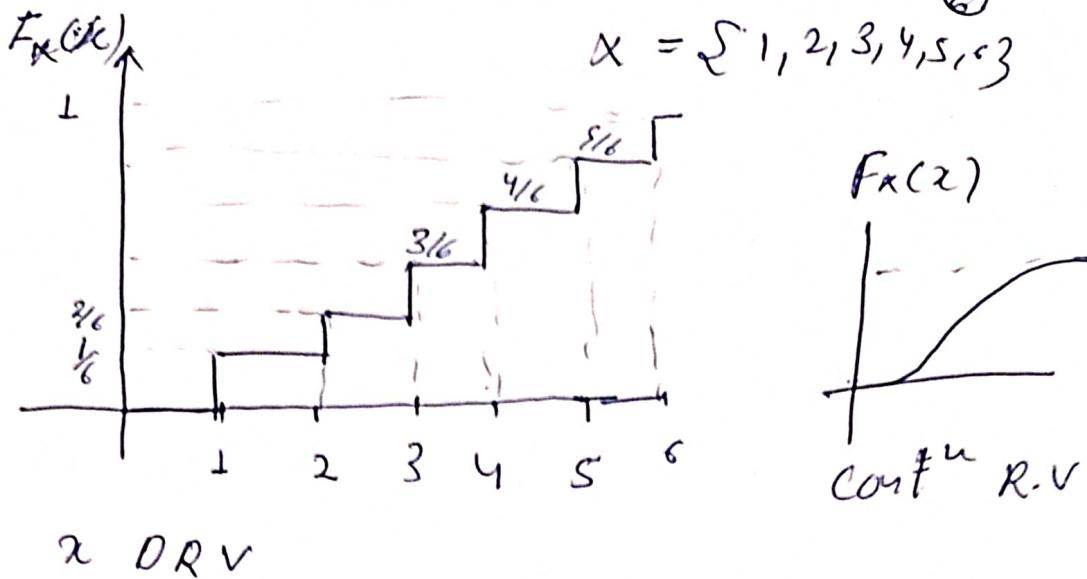
discrete random variable

when image is discontinuous then discrete random var.

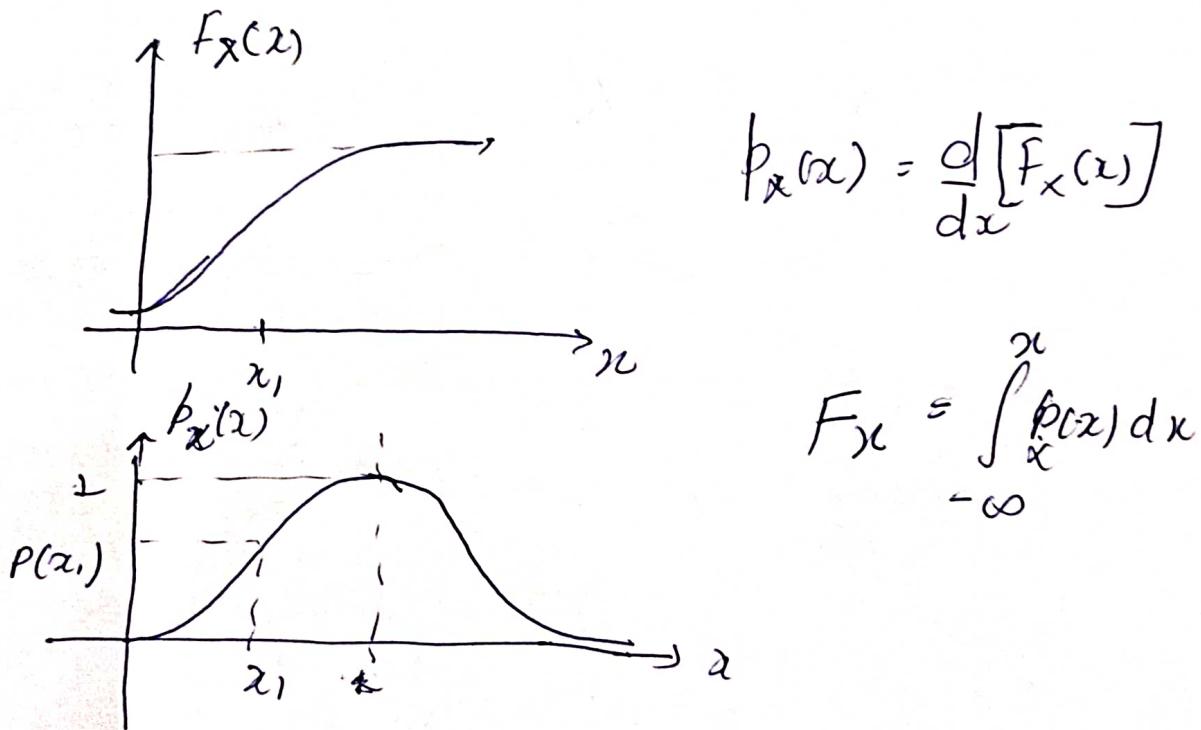
Probability Distribution function / Cumulative Distribution.

$$F_x(x) = P(X \leq x_1) \quad \begin{matrix} \downarrow \\ \text{probability of random process} \\ \text{from } -\infty \text{ to } x. \end{matrix}$$

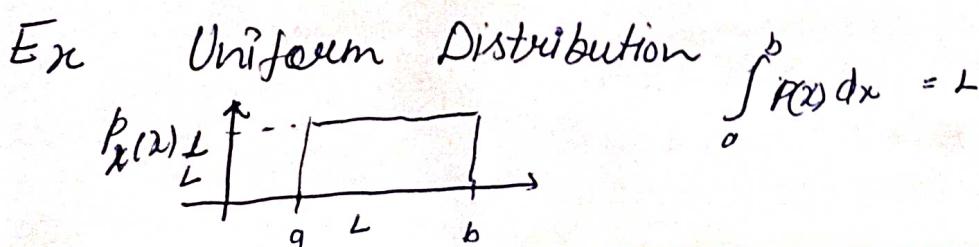
CDF \rightarrow non decreasing function

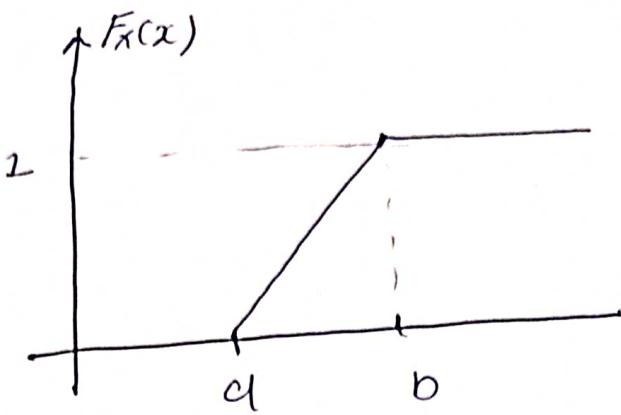


Pdf : probability density function



$$\begin{aligned} P(x_1 \leq X \leq x_2) &= F_X(x_2) - F_X(x_1) \\ &= \int_{x_1}^{x_2} p(x) dx \end{aligned}$$



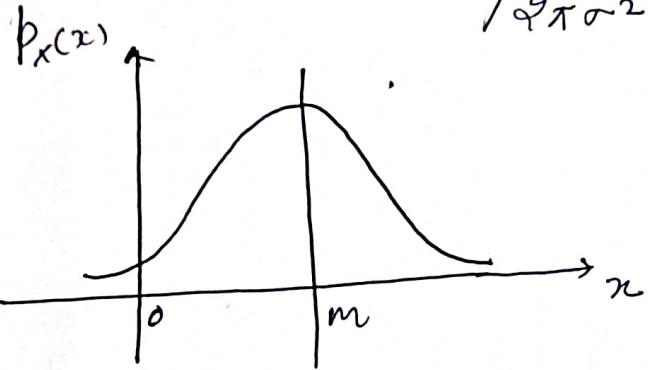


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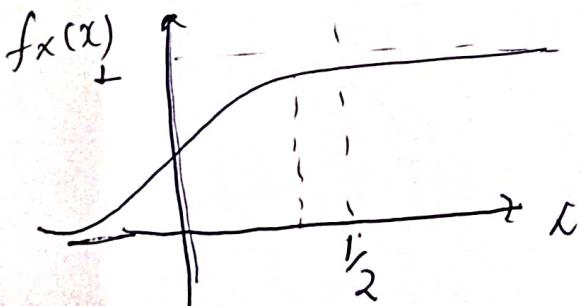
Gaussian distribution

$$P_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-m)^2}{2\sigma^2}}$$

m = mean
 σ^2 = variance



$$\sigma_1 > \sigma_2$$



multiple r.v.

$$F_{X_1, X_2}(x_1, x_2) = P(X_1 \leq x_1, X_2 \leq x_2)$$

$$P_{X_1, X_2} = \frac{\partial}{\partial x_1 \partial x_2} F_{X_1, X_2}(x_1, x_2)$$

$$F_{X_1, X_2} = \int_{-\infty}^{x_1} \int_{-\infty}^{x_2} P_{X_1, X_2}(y_1, y_2) dy_1 dy_2$$

$$F_{x_1/x_2}(x_1 | x_2 = x_2) = \frac{\int_{-\infty}^{x_1} P_{x_1|x_2}(y, x_2) dy}{P_{x_2}(x_2)}$$

$$\begin{aligned} p_{x_1|x_2}(x_1 | x_2 = x_2) &= \left. \frac{\partial F(x/x_2)}{\partial x} \right|_{x=x_1} \\ &= \frac{p_{x_1|x_2}(x_1, x_2)}{p_{x_2}(x_2)} \end{aligned}$$

Independent r.v

$$p_{x_1, x_2}(x_1, x_2) = p_{x_1}(x_1) p_{x_2}(x_2)$$

$$F_{x_1, x_2}(x_1, x_2) = F_{x_1}(x_1) F_{x_2}(x_2)$$

$$2_{40} \quad \sum_{i=1}^5 -$$

Mean / Expectation

$$\frac{0x2 + 1x5 + 2x6 + -1x5}{40}$$

$$x_i p_x(x)$$

$$\mu_x = E(x) = \bar{x} = \sum_{i=1}^n x_i p_i$$

D. r.v

$$\int \mu_x = \int x p(x) dx$$

$$C. r.v$$

$$\sigma_x^2 = \int_{-\infty}^{\infty} (x - \mu_x)^2 p(x) dx = E[(x - \mu_x)^2] = \sigma_x^2$$

$$E(x^2) = \int x^2 p(x) dx . \text{ second moment of r.v } x$$

$$\int x^n p(x) dx - n^{\text{th}} \text{ moment of r.v }$$

$$\begin{aligned}
 E[(x - \bar{u}_x)^2] &= E(x^2 + u_x^2 - 2x\bar{u}_x) \\
 &= E(x^2) + E(u_x^2) - 2\bar{u}_x E(x) \\
 &= E(x^2) + u_x^2 - 2u_x^2
 \end{aligned}$$

$$\boxed{\sigma_x^2 = E(x^2) - u_x^2}$$

standard deviation

Covariance - varies w.r.t mean

x y

$E[xy]$: ρ_{xy} correlation

$$\begin{aligned}
 C_{xy} &= E[(x - \bar{u}_x)(y - \bar{u}_y)] \\
 &= E(xy - x\bar{u}_y - y\bar{u}_x + \bar{u}_x\bar{u}_y) \\
 &= E(xy) - \bar{u}_y E(x) - \bar{u}_x E(y) + \bar{u}_x \bar{u}_y \\
 &= E(xy) - 2\bar{u}_x \bar{u}_y + \bar{u}_x \bar{u}_y
 \end{aligned}$$

$$\boxed{C_{xy} = E[xy] - \bar{u}_x \bar{u}_y}$$

if $C_{xy} = 0$ then x and y are uncorrelated

$E(xy) = \mu_{xy} = 0$ then orthogonal / independent

Covariance Matrix

Vector \rightarrow underline

$$\begin{matrix} \underline{x}_1 & \underline{x}_2 & \dots & \underline{x}_n \\ \downarrow & \downarrow & & \downarrow \\ \underline{u}_1 & \underline{u}_2 & & \underline{u}_n \end{matrix}$$

$$\underline{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad \underline{u} = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix}$$

covariance b/w x_i, x_j

$$E[(x_i - \bar{u}_i)(x_j - \bar{u}_j)]$$

$$E[(\underline{x} - \underline{u})(\underline{x} - \underline{u})^T]$$

$$\begin{bmatrix} x_1 - \bar{u}_1 \\ x_2 - \bar{u}_2 \\ \vdots \\ x_n - \bar{u}_n \end{bmatrix} \begin{bmatrix} (x_1 - \bar{u}_1) & (x_2 - \bar{u}_1) & \dots & (x_n - \bar{u}_1) \\ (x_1 - \bar{u}_2) & (x_2 - \bar{u}_2) & \dots & (x_n - \bar{u}_2) \\ \vdots & \vdots & \ddots & \vdots \\ (x_1 - \bar{u}_n) & (x_2 - \bar{u}_n) & \dots & (x_n - \bar{u}_n) \end{bmatrix}$$

$$= \begin{bmatrix} E[(x_1 - \bar{u}_1)(x_1 - \bar{u}_1)] & E[(x_1 - \bar{u}_1)(x_2 - \bar{u}_2)] & \dots & E[(x_1 - \bar{u}_1)(x_n - \bar{u}_n)] \\ E[(x_2 - \bar{u}_2)(x_1 - \bar{u}_1)] & \dots & & E[(x_2 - \bar{u}_2)(x_n - \bar{u}_n)] \\ \vdots & & & \vdots \\ E[(x_n - \bar{u}_n)(x_1 - \bar{u}_1)] & E[(x_n - \bar{u}_n)(x_2 - \bar{u}_2)] & \dots & E[(x_n - \bar{u}_n)(x_n - \bar{u}_n)] \end{bmatrix}$$

$$= \begin{bmatrix} \sigma_{x_1}^2 & c_{x_1 x_2} & \dots & c_{x_1 x_n} \\ c_{x_2 x_1} & \sigma_{x_2}^2 & \dots & c_{x_2 x_n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{x_n x_1} & c_{x_n x_2} & \dots & \sigma_{x_n}^2 \end{bmatrix}$$

x_1, x_2, \dots, x_n u_1, u_2, \dots, u_n

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad u = \begin{bmatrix} u_1 \\ \vdots \\ u_n \end{bmatrix}$$

$$\mu_{ij} = E_x [x_i \cdot u_j] (x_j \cdot u_i)]$$

$p \rightarrow$ probability distribution
 $P \rightarrow$ probability

$$C_{xx} = \begin{bmatrix} \mu_{11}, \mu_{12}, \dots, \mu_{1n} \\ \mu_{21}, \mu_{22}, \dots, \mu_{2n} \\ \vdots & \vdots & \vdots \\ \mu_{n1}, \mu_{n2}, \dots, \mu_{nn} \end{bmatrix}$$

$$u_i j = \mu_{ij}$$

$$\mu_{ii} = \sigma_i^2 \text{ Symmetric Matrix}$$

$$F_y(y) = P(Y \leq y)$$

$$y = ax + b$$

$$\leq P(ax + b \leq y)$$

$$P\left(x \leq \frac{y-b}{a}\right) = F_x\left(\frac{y-b}{a}\right)$$

$$F_y(y) = f_x\left(\frac{y-b}{a}\right)$$

$$p_y(y) = \frac{d}{dy} F_y(y)$$

$$= \frac{d}{dy} \int f_x\left(\frac{y-b}{a}\right)$$

$$= \frac{1}{a} p_x\left(\frac{y-b}{a}\right)$$

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multiple r.v

$$\underline{x} = [x_1 \dots x_n]$$

$$y_i = g_i(\underline{x})$$

$$g_i^{-1}(y_i) = x_i$$

$$\underline{x} = f_i(y)$$

$$J = \begin{bmatrix} \frac{\partial f_1}{\partial y_1} & \frac{\partial f_1}{\partial y_2} & \dots & \frac{\partial f_1}{\partial y_n} \\ \frac{\partial f_2}{\partial y_1} & \dots & \dots & \frac{\partial f_n}{\partial y_2} \\ \vdots & & & \frac{\partial f_n}{\partial y_n} \end{bmatrix}_{n \times n}$$

$$P_Y(y) = P_X(x|J)$$

$$P_Y(y) = P_X[f(y)] | J$$

Jacobian Matrix

Discrete Random process

$$X(t) \quad t_1 < t_2 < t_3$$

$$\begin{array}{c} +-----+ \\ t_1 \quad t_2 \quad t_3 \end{array}$$

$$P(x_{t_1}, x_{t_2}, x_{t_3})$$

$$\begin{array}{c} +-----+ \\ t_1 \quad t_2 \quad t_3 \\ t_1' = t_1 + \tau \quad t_2' = t_2 + \tau \quad t_3' = t_3 + \tau \end{array}$$

$$P(x_{t_1'}, x_{t_2'}, x_{t_3'})$$

if PDT are equal then we call random process
strictly stationary

$$\begin{array}{c} +-----+ \\ 100 \quad 900 \\ 1 \quad -1000 \end{array}$$

$$E[x(n)] = \mu \rightarrow \text{first order stationary}$$

Correlation

$$R_{xy} = E[xy]$$

$$R_{xy}(k) = E[x(n)y(n-k)]$$

1st & 2nd by Kullback

$$\text{discrete } \phi(t_1, t_2) = E[x_{t_1} y_{t_2}]$$

Auto Correlation

$$R_x(k) = E[x(n)x(n-k)]$$

$$\phi_{xx}(t_1, t_2) = E(x(t_1) x(t_2))$$

$$\phi_{xx}(t_1, t_1 + \tau) = E[x(t) x(t+\tau)]$$

$$= \phi(\tau), R_{xx}(k) \quad \begin{cases} \text{1st order} \\ \text{1st order - const} \\ \text{2nd - corr}^n \end{cases}$$

$R_{xx}(k)$ corr depend only on time gap

R or time delay τ in cont signal

$\phi_{xx}(\tau) = \phi(\tau)$ - 2nd order stationary

if any random process ~~stays~~ obeys

- 1st order stationary

$$E[x(k)] = \mu_x$$

$$E[x(t)] = \mu_x$$

and 2nd Order

b/c

$$\phi(z) = E[x(t)x(t-z)]$$

$$R_{xx}(k) = E[x(n)x(n-k)]$$

if both satisfy
then we call process is called
WSS - wide sense stationary (by default)

IID - independent & identical distribution.

$$\overbrace{x_1, x_2, \dots, x_n}^{\text{independent}} \rightarrow x_1 \leftarrow \begin{array}{l} \text{mean } \mu \\ \text{variance } \sigma^2 \end{array}$$
$$x_2 \leftarrow \begin{array}{l} \text{mean } \mu \\ \text{var } \sigma^2 \end{array}$$
$$E[x(n)x(n-k)] = N\delta(k)$$

$$K=0, E[x(n)^2] = \sigma^2$$

$$H_{xx}(k) = N\delta(k)$$

$$P(x_1, x_2, \dots, x_n) = p(x_1)p(x_2)\dots p(x_n)$$

$$\cancel{x_1, x_2, \dots, x_n}$$

Uncorrelated \Rightarrow covariance = 0

Independence \Rightarrow corr = 0

$$x_1, x_2, \dots, x_n$$

$$x_i \sim N(0, \sigma^2)$$

$$N(\mu, \sigma^2)$$

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$$M = \begin{bmatrix} \sigma^2 & 0 & 0 & \dots & 0 \\ 0 & \sigma^2 & 0 & \dots & 0 \\ 0 & 0 & \sigma^2 & \dots & 0 \\ 0 & \dots & \dots & \sigma^2 & 0 \\ 0 & 0 & \dots & \dots & \sigma^2 \end{bmatrix} = \sigma^2 I_n$$

$$\mu_1 = E[x_1 x_1]$$

$$= E[x_1^2]$$

$$= \sigma_x^2 = r$$

$$R_{xx}(k) = \frac{1}{N} \sum_{n=1}^{N-1} s(x)$$

Gen $P_x(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

$$P_{x_1 x_2 \dots x_n}(x_1, x_2, \dots, x_n)$$

General

M = covariance matrix

$$- (x-y)^T M^{-1} (x-y)$$

$$P_{x_1 x_2 \dots x_n}(x_1, x_2, \dots, x_n) = \frac{1}{\sqrt{2\pi \det(M)}^N} e^{\frac{1}{2} \sum_{i,j} M_{ij} x_i x_j}$$

IID

$$P_{x_1 x_2 \dots x_n}(x_1, x_2, \dots, x_n) = P_{x_1}(x_1) P_{x_2}(x_2) \dots P_{x_n}(x_n)$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x_1-\mu)^2}{2\sigma^2}} \dots \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x_N-\mu)^2}{2\sigma^2}}$$

$$= \frac{1}{(2\pi\sigma^2)^N} e^{-\frac{N}{2\sigma^2} (x-\mu)^T (x-\mu)}$$

Power Spectral Density

$$\phi(\tau) = E[x(t)x(t-\tau)]$$

FT of $\phi(\tau)$

$$\phi(f) = \int_{-\infty}^{\infty} \phi(\tau) e^{-j2\pi f \tau} d\tau$$

$$\phi(\tau) = \int_{-\infty}^{\infty} \phi(f) e^{j2\pi f \tau} df$$

Small \rightarrow

$$\phi(0) = \int_{-\infty}^{\infty} \phi(f) e^0 df$$

$$= \int_{-\infty}^{\infty} \phi(f) df$$

$$\phi(0) = E[x(t)^2]$$

= power ~~spectral density~~ of signal

$\phi(f) \rightarrow$ is called / FT of $\phi(\tau)$ / FT of Autocorrelation

$$\phi(\tau) = E[x(t)x(t-\tau)]$$

$$\phi(-\tau) = E[x(t)x(t+\tau)]$$

$$= E[x(t-\tau)x(t)]$$

$$= \phi(\tau)$$

for Complex Signal

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$$\begin{aligned}\phi(t_1, t_2) &= \frac{1}{2} E[x(t_1) x^*(t_2)] \\ &= \frac{1}{2} E[x(t) x^*(t-\tau)]\end{aligned}$$

Q: What is PSD of IIO distributed random process.

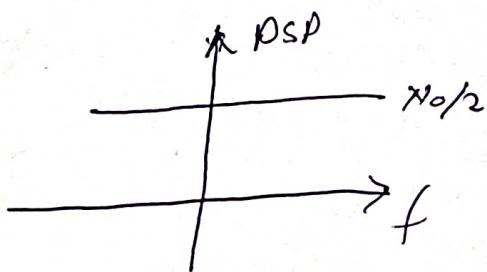
$$R_{xx}(k) = \frac{N_0}{2} S(k)$$

$$\phi(z) = \frac{N_0}{2} S(z)$$

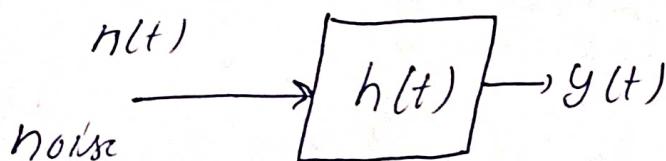
$$\text{PSD } \Phi(f) = \int_{-\infty}^{\infty} \phi(z) e^{-j 2\pi f z} dz$$

$$= \int_{-\infty}^{\infty} \frac{N_0}{2} S(z) e^{-j 2\pi f z} dz$$

$$\begin{aligned}&= \frac{N_0}{2} \text{ constant} \\ &= 10^{-5} \frac{\text{watt}}{\text{Hz}}\end{aligned}$$

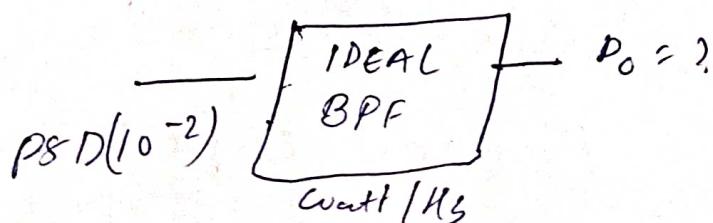


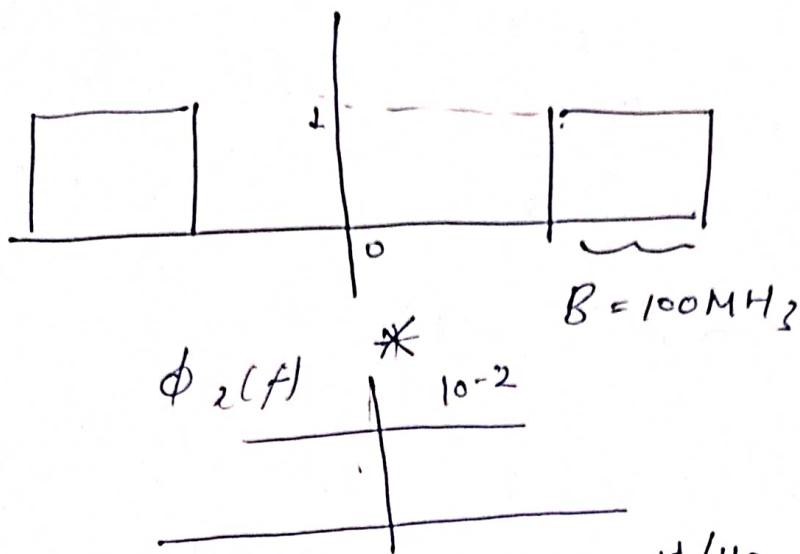
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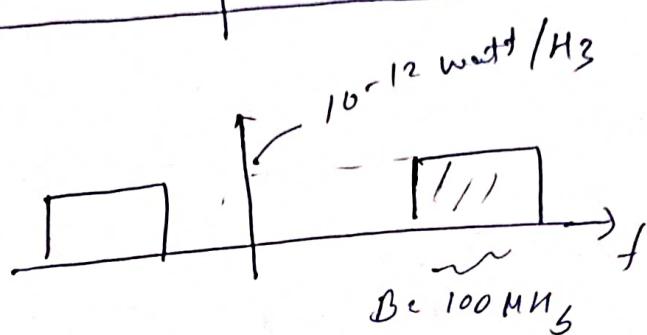
$$\Phi_y(f) = |H(f)|^2 \Phi_h(f)$$

Q: A Noise signal having PSD 10^{-12} watt/Hz given to a ideal BPF either 100 MHz BW find output power





$$10^{-12} \\ 100 \times 10^6 \\ 10^8$$



$$P_o = \int_{-\infty}^{\infty} \phi_2(f) df$$

$$\Rightarrow 2 \times 10^{-12} \times 10^8$$

$$P = 2 \times 10^{-4} \text{ watt}$$

$$P = 0.2 \text{ mW}$$

Noise is uncorrelated PSD

Question: Prove that PSD $\phi(e^{j\omega})$ of a signal $x(\omega)$ is real for (real valued signal)

$$\begin{aligned}
 \phi(e^{j\omega}) &= \text{DTFT of } x(k) R_{xx}(k) \\
 &= \sum_{k=-\infty}^{\infty} R_{xx}(k) e^{-j\omega k} \\
 &= R_{xx}(0) + \sum_{k=1}^{\infty} R_{xx}(k) e^{-j\omega k} + \sum_{k=1}^{\infty} \overline{R_{xx}(k)} e^{-j\omega k} \\
 &= " + " + \sum_{k=1}^{\infty} R_{xx}(-k) e^{j\omega k} \\
 &= " + " + \left(\sum_{k=1}^{\infty} R_{xx}(k) e^{-j\omega k} \right)^*
 \end{aligned}$$

Hemission Symmetry

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$$R_{xx}(-k) = E[x(n)x(n+k)] \\ = E[x(n-k)x(k)] = R_{xx}(k)$$

$$R_{xx}(k) = R_{xx}^*(-k)$$

$$\phi(e^{j\omega f}) = R_{xx}(0) + \sum_{k=1}^{\infty} R_{xx}(k) e^{-jk\omega k} + \left(\sum_{k=1}^{\infty} R_{xx}(k) e^{-jk\omega k} \right)^*$$
$$= R_{xx}(0) + 2 \sum_{k=1}^{\infty} \operatorname{Re} [R_{xx}(k) e^{-jk\omega k}]$$

Q: 2: A_i $i = 1, 2, 3, 4$ B_j $j = 1, 2, 3$
Event 1 E_2 \hookrightarrow outcome

$$P(A_1, B_1) = 0.1 \quad P(A_1, B_2) = 0.08 \quad P(A_1, B_3) = 0.13$$

$$P(A_2, B_1) = 0.05 \quad P(A_2, B_2) = 0.03 \quad P(A_2, B_3) = 0.09$$

$$P(A_3, B_1) = 0.05 \quad P(A_3, B_2) = 0.12 \quad P(A_3, B_3) = 0.14$$

$$P(A_4, B_1) = 0.11 \quad P(A_4, B_2) = 0.04 \quad P(A_4, B_3) = 0.06$$

Determine marginal probability $P(A_i) \stackrel{i=1,2,3,4}{=} P(B_j) \stackrel{j=1,2,3}{=}$

Sol^u

$$P(A_i) = \sum_{j=1}^3 P(A_i, B_j) \stackrel{i=1,2,3,4}{=}$$

$$P(A_1) = \sum_{j=1}^3 P(A_1, B_j) = P(A_1, B_1) + P(A_1, B_2) + P(A_1, B_3) \cancel{+ P(A_1, B_4)} \\ = 0.31$$

$$P(A_2) = 0.17 \quad P(A_3) = 0.32 \quad P(A_4) = 0.21$$

$$P(B_i) = \sum_{i=1}^4 P(A_i, B_i)$$

$$P(B_1) = \sum_{i=1}^4 P(A_i, B_1) = 0.1 + 0.05 + 0.05 + 0.11 = 0.31$$

$$P(B_2) = 0.27 \quad P(B_3) = 0.42$$

$$H(W) = P(A_i)P(B_j)$$

Q: Consider a r.v Y defined as $Y = ax^3 + b$ (14)
 $a > 0$

where x is a Gaussian r.v with pdf $P_x(x)$.

Determine PDF of Y in terms of PDF of X

Solⁿ. $F_Y(y) = P(Y \leq y)$

$$= P(ax^3 + b \leq y)$$

$$= P\left(x \leq \left(\frac{y-b}{a}\right)^{\frac{1}{3}}\right)$$

$$= F_X\left[\left(\frac{y-b}{a}\right)^{\frac{1}{3}}\right]$$

Now $p_Y(y) = \frac{d}{dy} F_X(y) = \frac{d}{dy} F_X\left[\left(\frac{y-b}{a}\right)^{\frac{1}{3}}\right]$

$$= P_x\left[\left(\frac{y-b}{a}\right)^{\frac{1}{3}}\right] \frac{d}{dy} \left(\frac{y-b}{a}\right)^{\frac{1}{3}}$$

$$= \frac{1}{\frac{3}{2}a} \left(\frac{y-b}{a}\right)^{\frac{2}{3}} \times P_x\left[\left(\frac{y-b}{a}\right)^{\frac{1}{3}}\right]$$

Q: $\overset{\text{Real part}}{x_R}, \overset{\text{Imaginary part}}{x_i}$ - statistical independent gaussian r.v

Rotational transformation of form

$$y_R + jy_i = [x_R + jx_i] e^{j\phi}$$

results another pair (y_R, y_i) of gaussian r.v

Show that (y_R, y_i) pair has same joint pdf as (x_R, x_i)

Sol^a $P(x_R, x_i) = P_x(x_R)P(x_i)$ \because independent

$$p_X(x_R) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x_R^2}{2\sigma^2}} \quad : \text{assume } \mu=0$$

$$p_X(x_R, x_i) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\left(\frac{x_R^2 + x_i^2}{2\sigma^2}\right)}$$

$$y_R + j y_i = (x_R + j x_i) e^{j\phi}$$

$$x_R + j x_i = (y_R + j y_i) e^{-j\phi}$$

$$= (y_R + j y_i) (\cos\phi - j \sin\phi)$$

$$x_R = y_R \cos\phi + y_i \sin\phi$$

$$x_i = -y_R \sin\phi + y_i \cos\phi$$

$$J = \begin{vmatrix} \frac{\partial x_R}{\partial y_R} & \frac{\partial x_i}{\partial y_R} \\ \frac{\partial x_R}{\partial y_i} & \frac{\partial x_i}{\partial y_i} \end{vmatrix} = \begin{vmatrix} \cos\phi & -\sin\phi \\ \sin\phi & \cos\phi \end{vmatrix} = 1$$

$$p_Y(y_R, y_i) = \frac{1}{|J|} p_X(y_R \cos\phi + y_i \sin\phi, -y_R \sin\phi + y_i \cos\phi)$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2} [(y_R \cos\phi + y_i \sin\phi)^2 + (-y_R \sin\phi + y_i \cos\phi)^2]}$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x_R^2 + y_i^2)}{2\sigma^2}}$$

2nd part

J.-E. Proakis → 2nd Chapter
Sampling + Sampling

Sampling : Continuous-time signal

Sampling

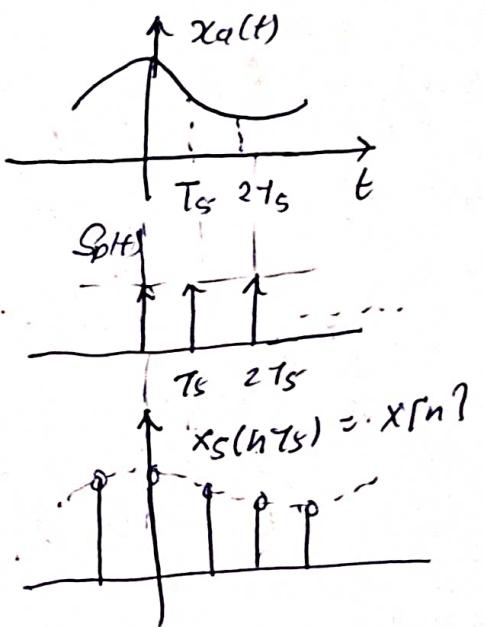
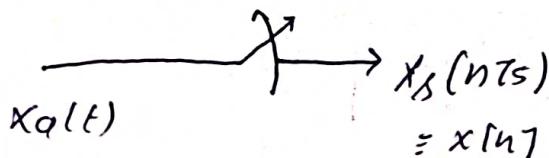
→ Discrete-time signal

↳ Discretizing time

Uniform sampling

T_s = Sampling period

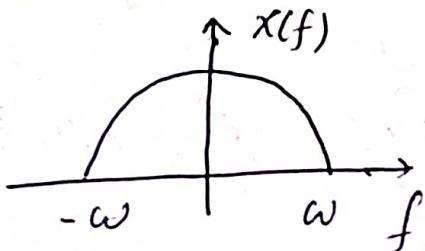
$\frac{1}{T_s} = f_s = \text{Sampling freq.}$



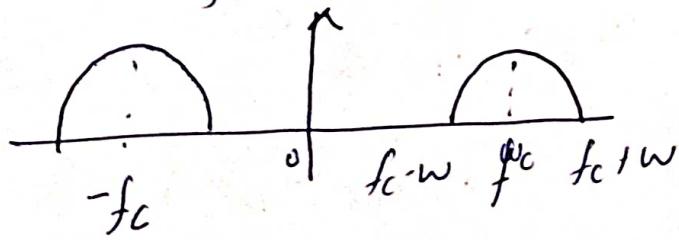
Question 1) Can we ~~reg~~ recover the original signal

2) Is there any loss of information.

Loss can be minimize if signal is band-limited.



$$|X(f)| = 0 \quad |f| \geq \omega$$



Nyquist Theorem / Rate

$f_s \geq 2\omega$ if sampling freq satisfy this condⁿ then we can recover the original signal from sampled sign

$$f_s = 2\omega \quad (\text{critical rate})$$

Q: The Covariance matrix of R.V x_1, x_2, x_3 is

(15)

$$\begin{bmatrix} u_{11} & 0 & u_{13} \\ 0 & u_{22} & 0 \\ u_{31} & 0 & u_{33} \end{bmatrix} \quad \begin{array}{l} \text{the linear} \\ \text{transformation} \\ \underline{y = Ax} \end{array} \quad A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 1 & 0 & 1 \end{bmatrix}$$

find covariance matrix of y

Soln $X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad \mu_x = \begin{bmatrix} u_{11} \\ u_{21} \\ u_{31} \end{bmatrix}$

Covariance matrix $\Sigma_X = E[(x - \mu_x)(x - \mu_x)^T]$

$$\Sigma_Y = E[(y - \mu_y)(y - \mu_y)^T]$$

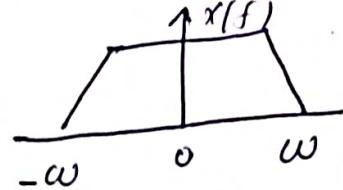
$$= E[(Ax - Au_x)(Ax - Au_x)^T]$$

$$\Rightarrow \Sigma_Y = E[A(x - \mu_x)(x - \mu_x)^T A^T]$$

$$= A E[(x - \mu_x)(x - \mu_x)^T] A^T$$

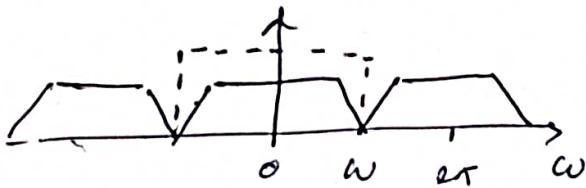
S-6 Eq 8m!

$$x_a(t) \xleftarrow{F.T} X(f)$$



(16)

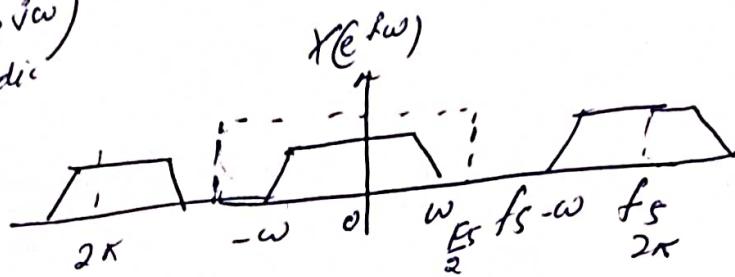
$$x(n) \xleftarrow{DTFT} X(e^{j\omega}) \text{ periodic}$$



Critical

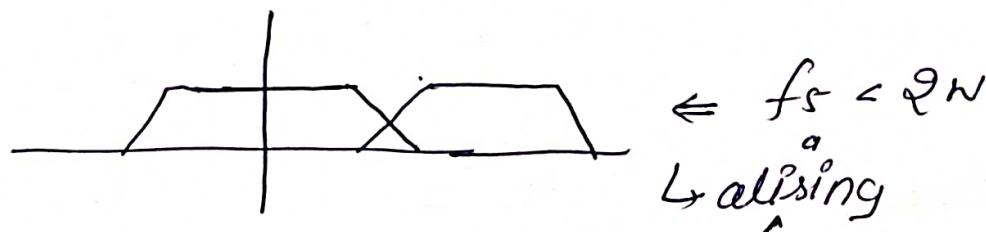
$$f_s = 2w$$

$$\frac{f_s}{2} = w$$

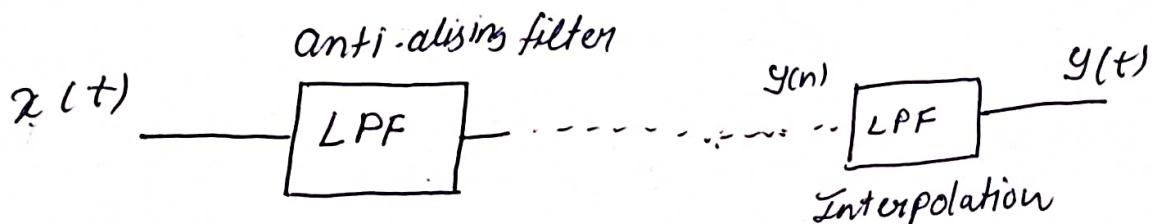


$$f_s - w \geq w$$

$$\Rightarrow f_s \geq 2w$$



anti-aliasing filter

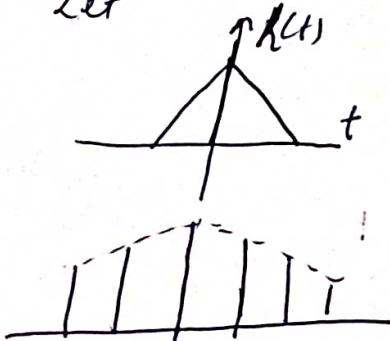


$$x_s[n] \xleftrightarrow{LPF} \hat{x}(t) \quad x_s(t) = \sum_{-\infty}^{\infty} x[n] \delta(t - nT_s)$$

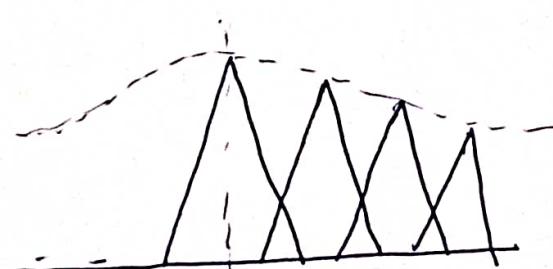
$$x(t) = \sum_{n=-\infty}^{\infty} x[n] T_s \delta(t - nT_s) \quad \text{Ideal Sampling}$$

$$x(n) \xrightarrow{h(t)} x(t) = \sum x(n) h(t - nT_s)$$

let



T_s

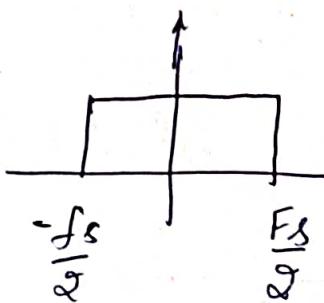


$$\hat{x}(t) = \sum_{n=-\infty}^{\infty} x(nT_s) h(t - nT_s)$$

$h(t) = ?$ *filter such that* $\hat{x}(t) = x(t)$
find $\hat{x}(f) = X(f)$

$$h(t) = \text{sinc}(f_s t) = \frac{\sin \pi f_s t}{\pi f_s t}$$

$$H(f) =$$



$$\hat{x}(f) = f_1 \left(\sum_{n=-\infty}^{\infty} x(nT_s) h(t - nT_s) \right)$$

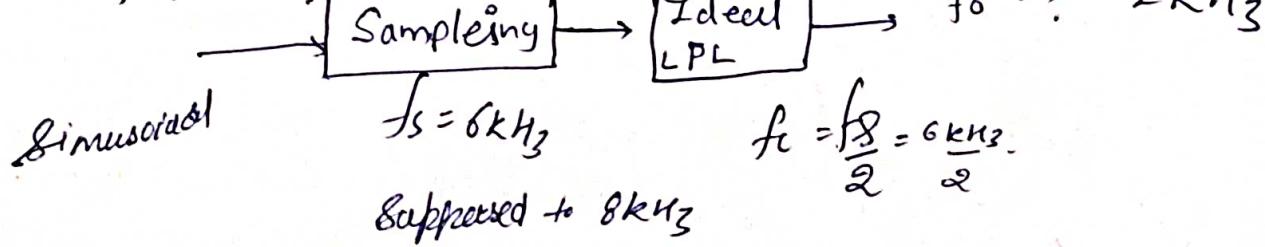
+
constan

$$= \sum_{n=-\infty}^{\infty} x(nT_s) e^{-j2\pi f_s n} \xrightarrow{\text{Fourier Transform}} X(e^{j\omega})$$

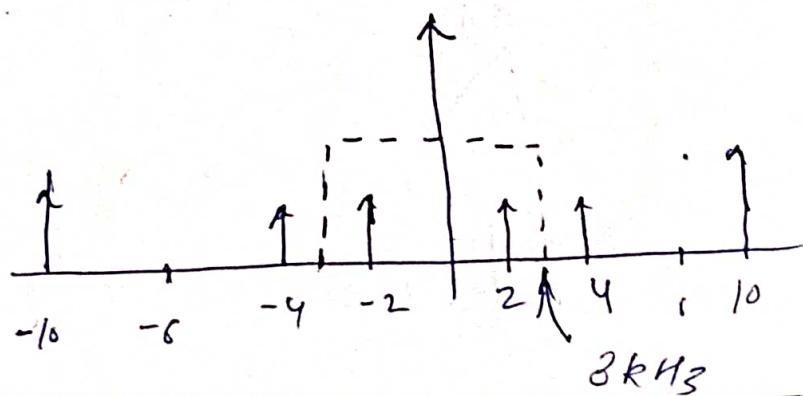
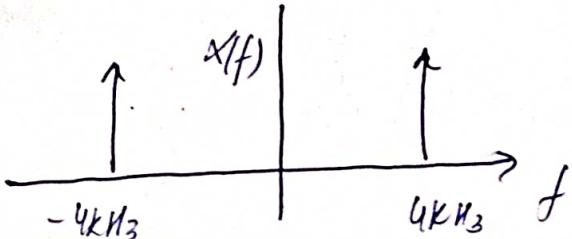
$$= X(f)$$

Ex Undersampling

$$f_m = 4kHz$$



$$x(t) = A \cos(\omega_m t)$$

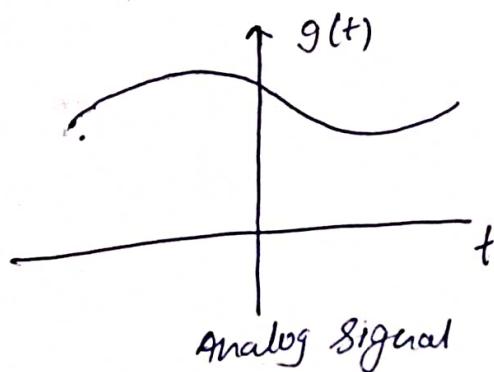


↳ Anti aliasing filter used to check sampling freq. (17)

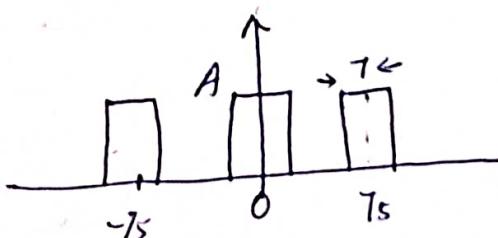
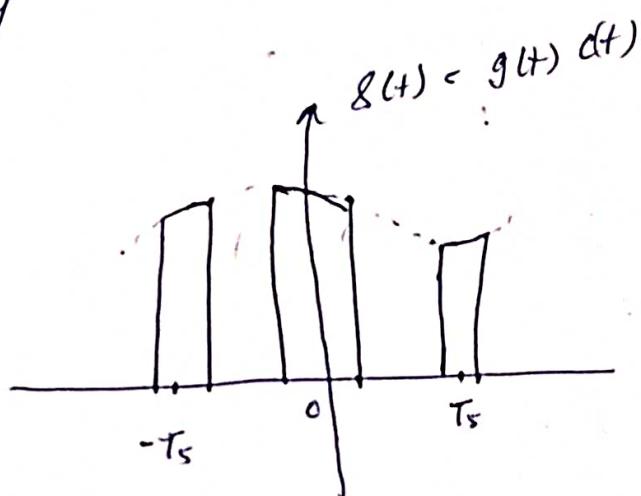
Practical Aspect of Sampling

- ↳ Sampling is accomplished by means of high speed switching transition circuit
- ↳ practically the switching time can not be zero [11]
- ↳ type of sampling

(1) Natural Sampling



(a) Analog Signal



Sampling function

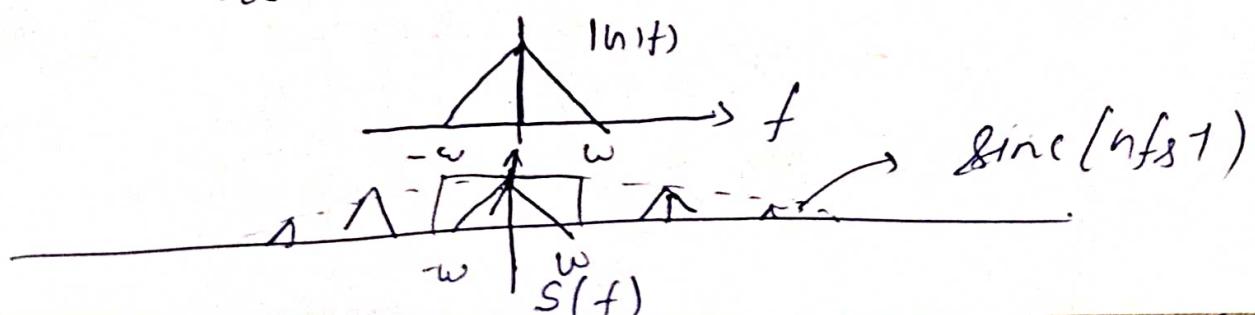
$$C(t) = \text{Fourier Series}$$

$$\rightarrow f_s T_A \cdot \sum C_n e^{j 2\pi n f_s t}$$

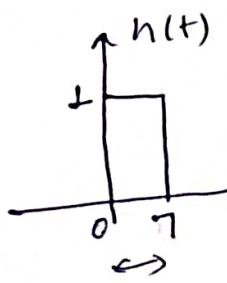
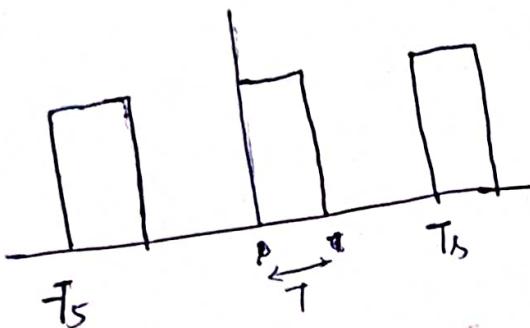
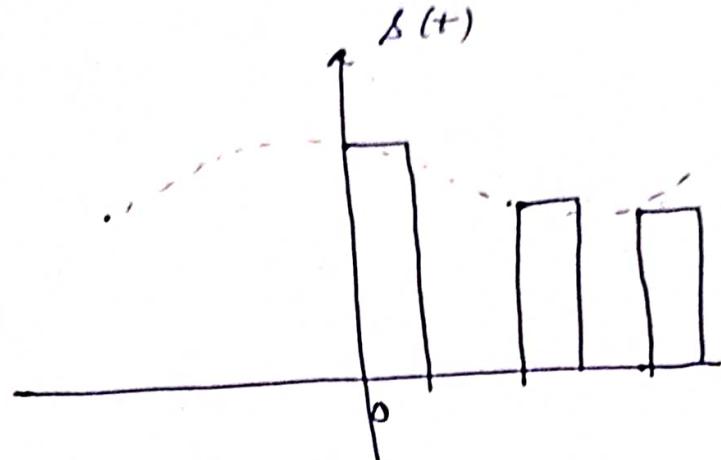
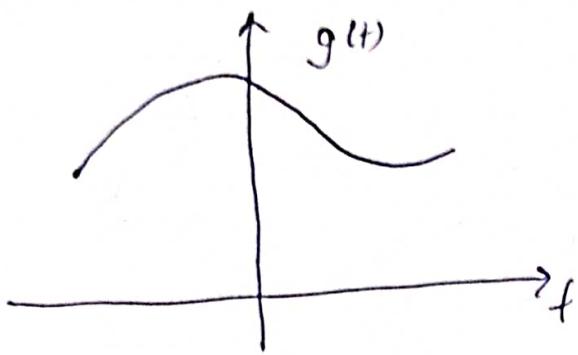
$$C_n = \text{sinc}(n f_s t)$$

$$\rightarrow S(t) = f_s T_A \sum_{-\infty}^{\infty} \text{sinc}(n f_s t) e^{j 2\pi n f_s t} g(t)$$

$$\Rightarrow S(f) = f_s T_A \sum_{-\infty}^{\infty} \text{sinc}(n f_s t) \cdot G(f - n f_s) \quad T_A = 1$$



G flat - Top Sampling / PULSE Amplitude modulator / sample & Hold (S/H)



$$\begin{aligned} h(t) &= \text{rect}\left(\frac{t - T/2}{T}\right) \\ &= \text{rect}\left(\frac{t}{T} - \frac{1}{2}\right) \end{aligned}$$

$$h(t) = \begin{cases} 1 & 0 \leq t \leq T \\ 0 & \text{otherwise} \end{cases}$$

* Ideal Sampling / Impulse Sampling

$$g_s(t) = \sum_{n=-\infty}^{\infty} g(nT_s) \delta(t - nT_s)$$

$$G_s(f) = f_s \sum_{-\infty}^{\infty} G(f - n f_s)$$

$$g_{st}(t) = \sum_{n=-\infty}^{\infty} g_s(t) \oplus h(t) \quad \leftarrow \text{flat top sampling}$$

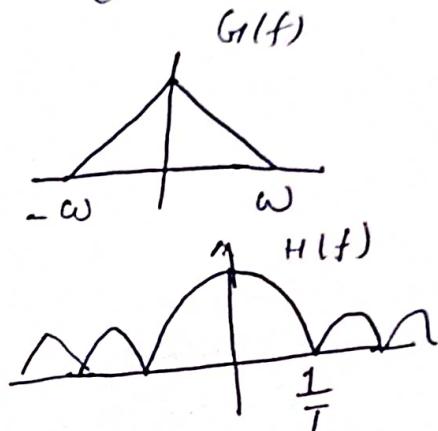
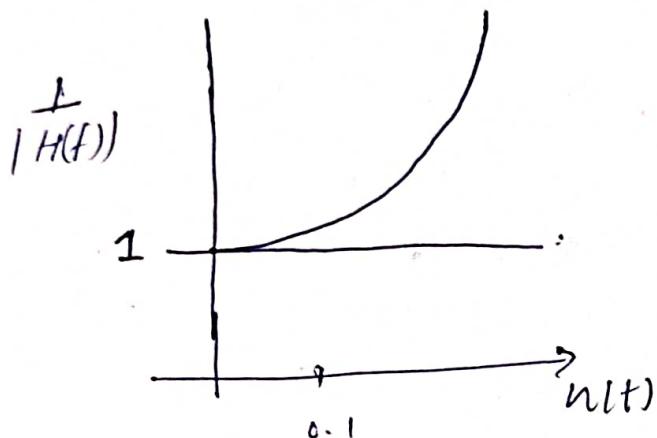
$$= \sum_{n=-\infty}^{\infty} g(nT_s) \delta(t - nT_s) \oplus h(t)$$

$$= \sum_{n=-\infty}^{\infty} g(nT_s) h(t - nT_s)$$

$$S(f) = G_s(f) H(f)$$

$$\Rightarrow f_s \sum H(f) G_s(f - nT_s)$$

$$H(f) = T \operatorname{sinc}(fT) e^{-2\pi fT \frac{1}{2}}$$

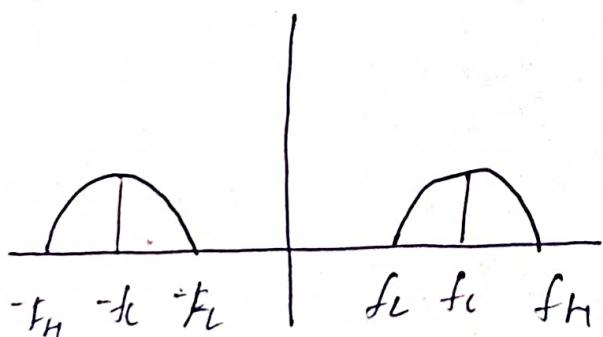


↳ allowed duty cycle $\tau_{px} = \frac{T}{T_s} = 0.1$

Sampling of Band pass Signal

Sampling Range f_H = highest freq

f_L = lowest freq $B = f_H - f_L$



$$f_s = 2B$$

If f_H or f_L is one of the Harmonics of f_s

$$f_H = 100 \text{ MHz}$$

$$f_L = 90 \text{ MHz}$$

$$B = 10 \text{ MHz}$$

Minimum Sampling frequency allowed is

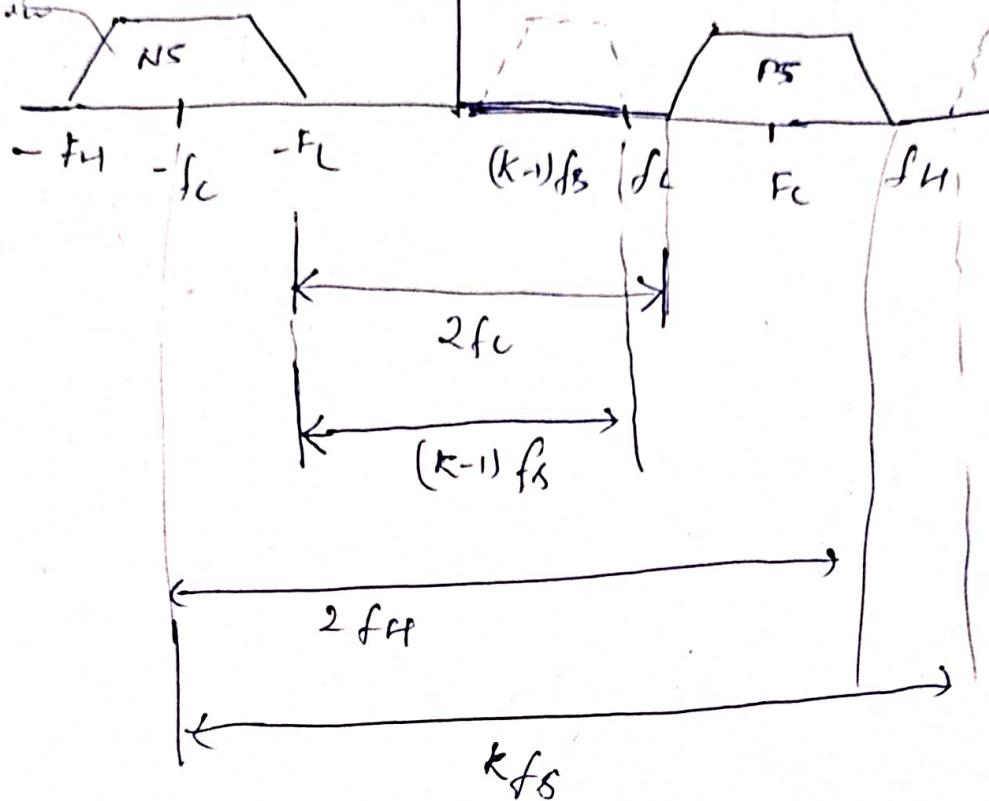
$$f_s = 2(f_H - f_L)$$

provided that either f_L or f_H is harmonic of f_s

$$f_H \neq kB$$

Negative

Spectrum



$$f_B \ll f_C$$

$$2f_L \geq (k-1)f_S$$

$$2f_H \geq kB$$

$$\Rightarrow \frac{2f_H}{k} \leq f_S \leq \frac{2f_L}{k-1}$$

$$\therefore f_{BL} = f_H - B$$

$$\frac{1}{f_S} \leq \frac{k}{2f_H} \Rightarrow (k-1) \leq \frac{k}{2f_H} (f_H - B)$$

$$(k-1)f_S \leq 2f_L \Rightarrow (k-1)f_S \leq 2(f_H - B)$$

$$k \leq \frac{f_H}{B}$$

$$k_{\max} = \frac{f_H}{B}$$

$$\therefore \frac{k-1}{k} \leq \frac{f_H - B}{f_H} \Rightarrow 1 - \frac{1}{k} \leq 1 - \frac{B}{f_H} \Rightarrow \frac{1}{k} \geq \frac{B}{f_H} \Rightarrow k \leq \frac{f_H}{B}$$

∴

$$k_{\max} = \frac{f_H}{B}$$

$$f_S \geq \frac{2f_H}{k}$$

Band pass Sampling Theorem.

(19)

A Band pass signal with High freq f_H and Bandwidth B can be recovered from its samples through a BPF filtering by sampling it with frequency

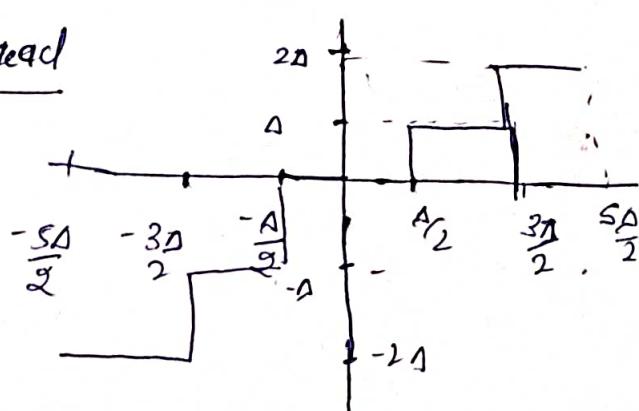
$$f_s = \frac{2f_H}{k} \text{ where } k \text{ is the largest integer not exceeding } \frac{f_H}{B}$$

Summary - 4 Sampling Ideal, Normal, flat top, BP

Quantization

↳ Describing Sample in Amplitude

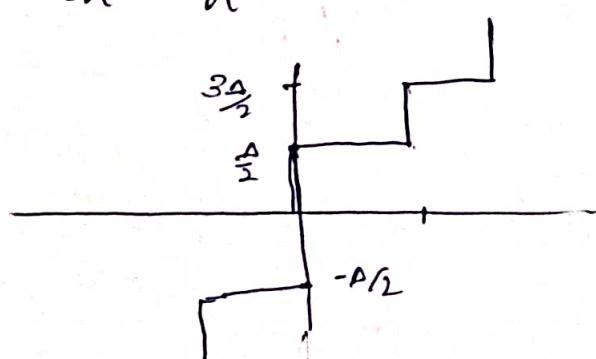
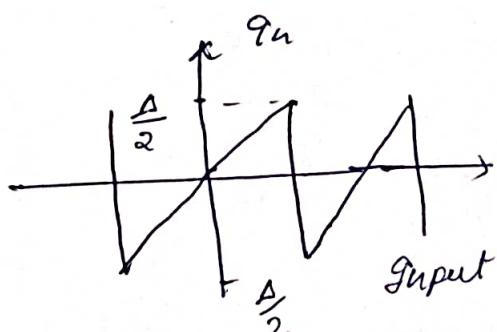
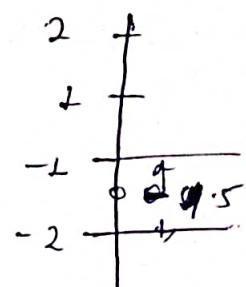
Midtread



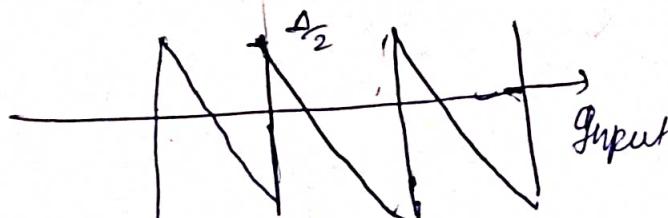
$$\tilde{x} = x_n + q_n$$

Quantization

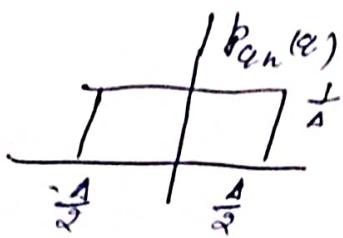
$$\text{Error. } q_n = \tilde{x}_n - x_n$$



mid size
origin mid b/w
size path



Max^m quantization Error = $\Delta/2$



Range $-\frac{\Delta}{2}$ to $\frac{\Delta}{2}$

$$p_{q_m}(x) = \text{pdf of } q_m = \begin{cases} \frac{1}{\Delta} & -\frac{\Delta}{2} \leq q_m \leq \frac{\Delta}{2} \\ 0 & \text{otherwise} \end{cases}$$

Mean of $q_m = 0$

$\therefore \text{MSE} = \sigma_{q_m}^2 = E(q_m^2) = \int_{-\frac{\Delta}{2}}^{\frac{\Delta}{2}} q^2 p(q) dq$

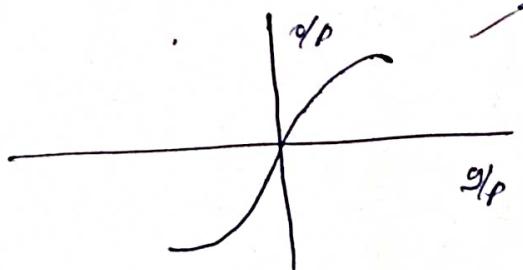
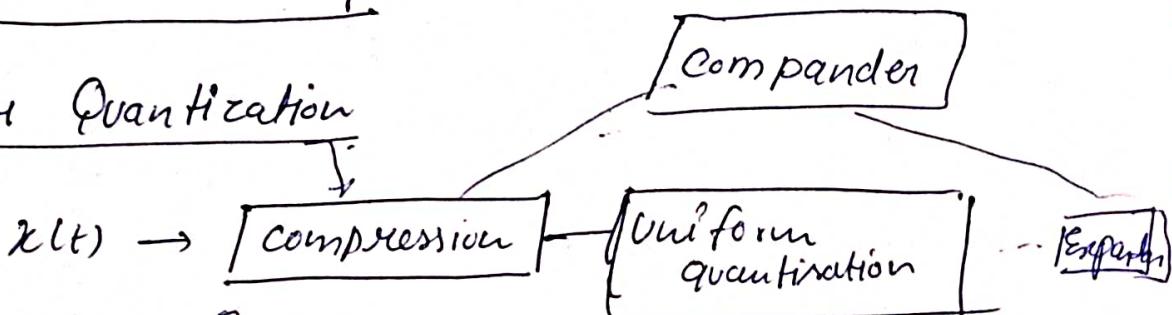
mean sqr error

$$= \int_{-\frac{\Delta}{2}}^{\frac{\Delta}{2}} q^2 \times \frac{1}{\Delta} dq = \frac{\Delta^2}{12}$$

less $\sigma \rightarrow$ bits ??

$$\boxed{\sigma_{q_m}^2 = \frac{\Delta^2}{12}}$$

Non-linear Quantization



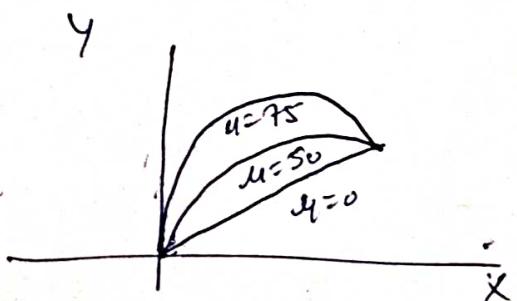
A - low - European

u - low \rightarrow American

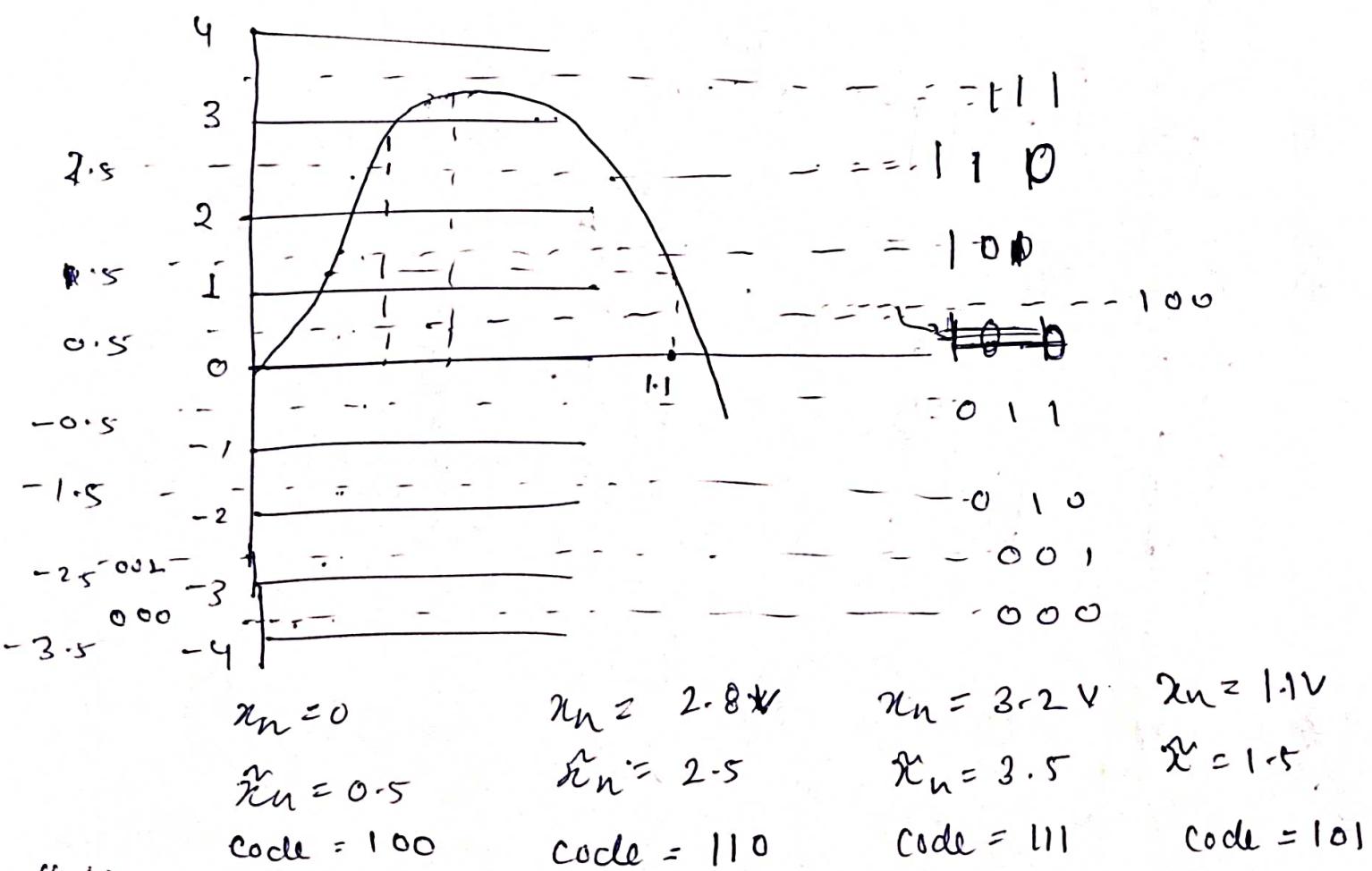
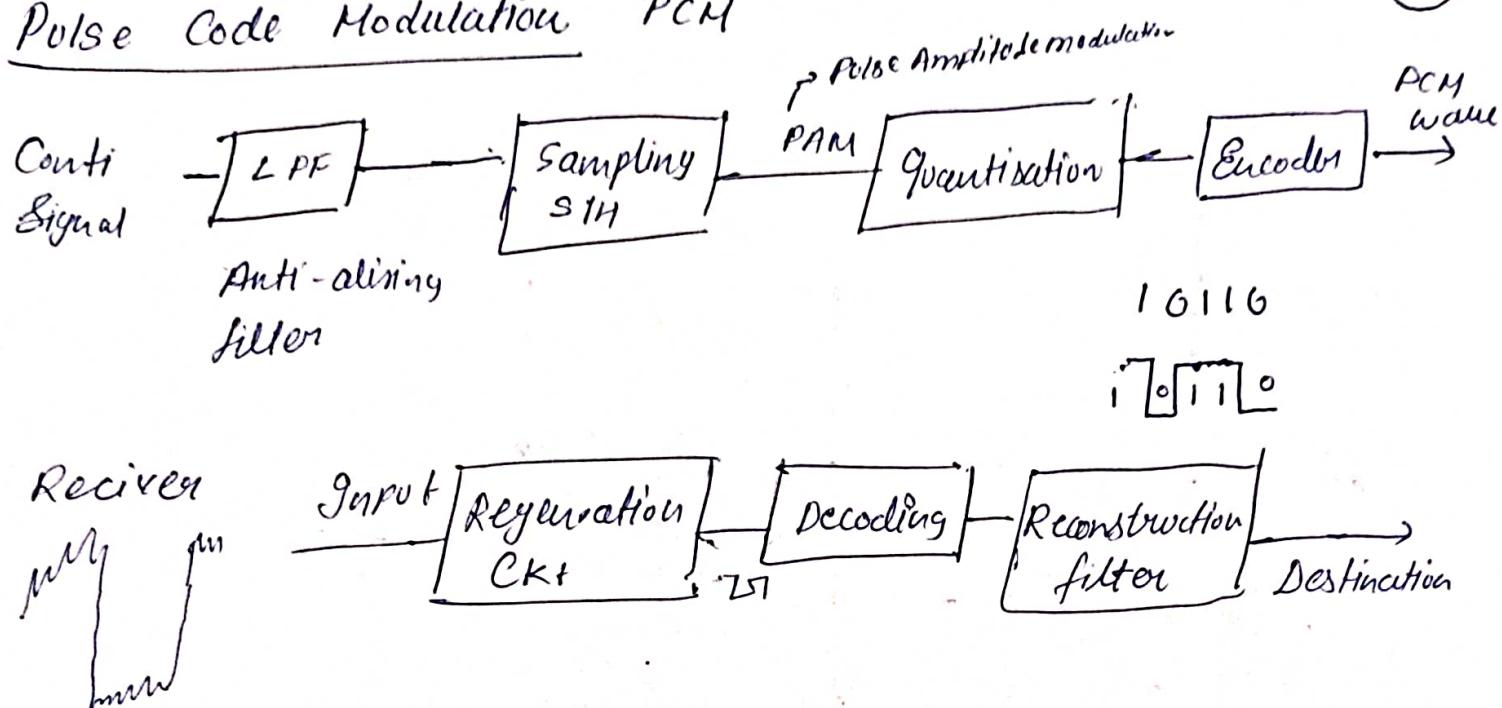


$$|y| = \frac{\log(1 + f(x))}{\log(1+x)} g_m(x)$$

0 < 25%



Pulse Code Modulation PCM



Line coding

Eg Audio Signal

Speech Signal

$0.3 - 3.3 \text{ kHz}$

$f_s = 8 \text{ kHz}$

8-bit PCM

Output bit rates =

$$R = 8 \text{ kHz} \times 8 \text{ bit}$$

$$= 64 \text{ k bit sec}$$

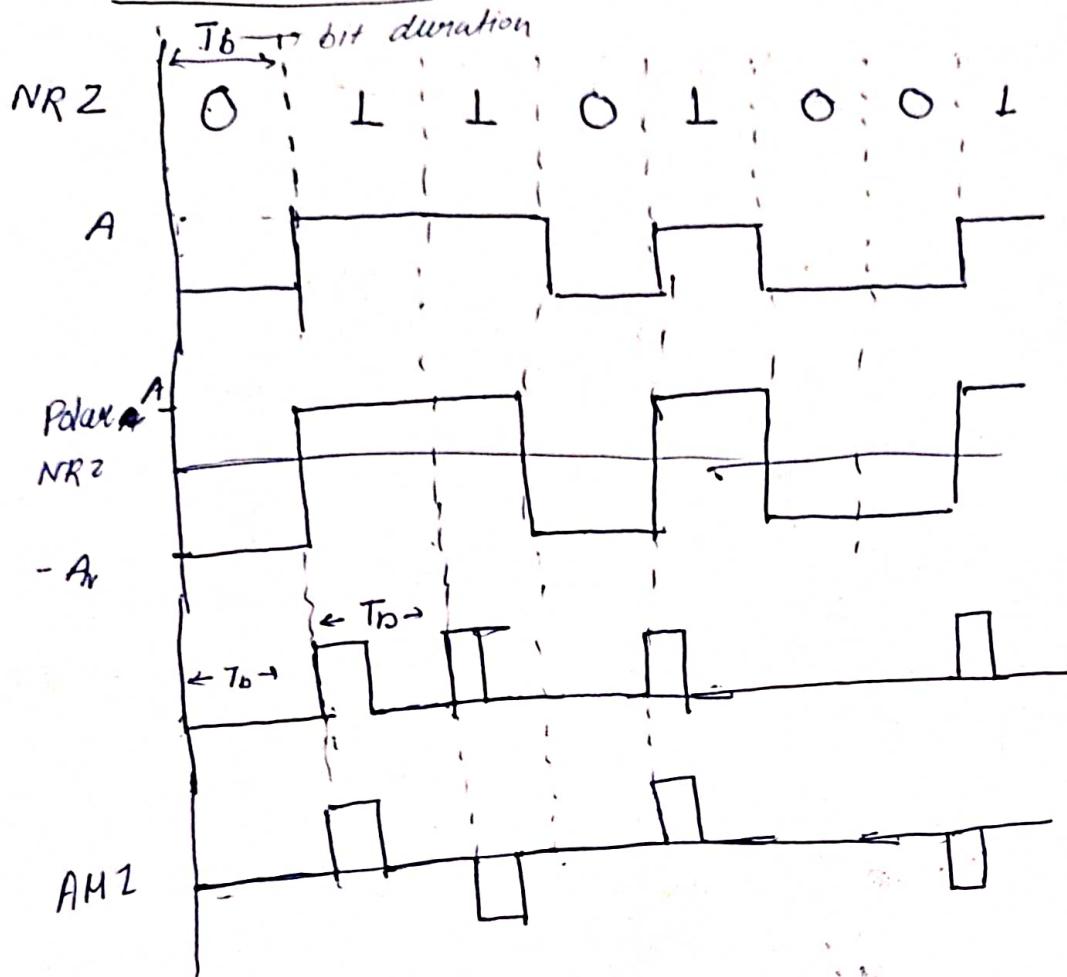
256 - levels

= 64 kbps

Line Coding

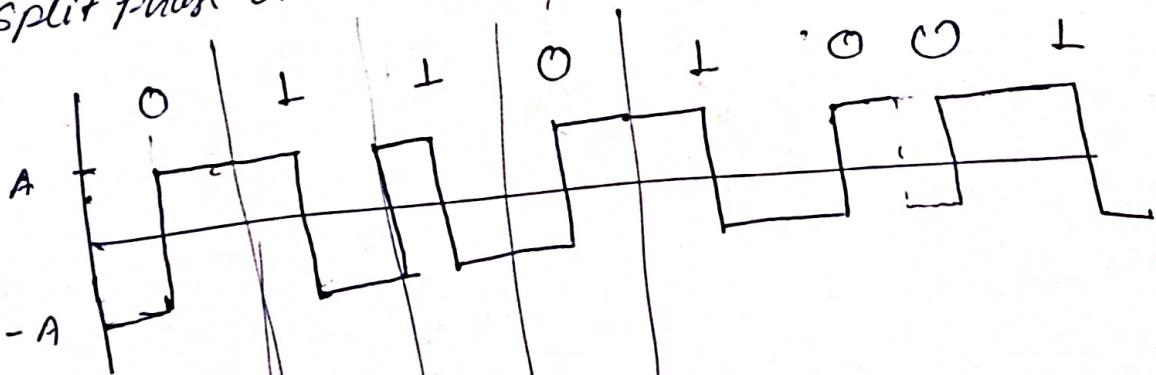
NRZ

Non Return to Zero



Alternate mark
Inversion
or
Bipolar return to
zero

Split phase or Manchester Code



DPCM - Differential PCM

$$PCM - R = n f_s$$

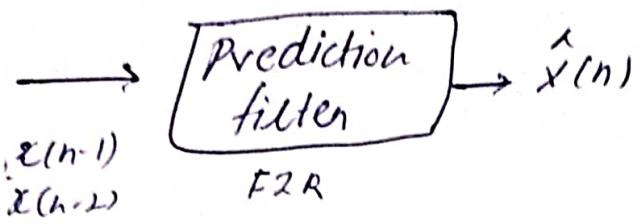
n = no of bits used to encode each sample

f_s = sampling freq.

$$e(n) = m(n T_s) - m((n-1) T_s)$$

$$m(n-1) + e(n) = m(n)$$

(21)



predictions predict signal
from past symbol

$$e(n) = m(n) - \hat{m}(n) \quad \text{predicted.}$$

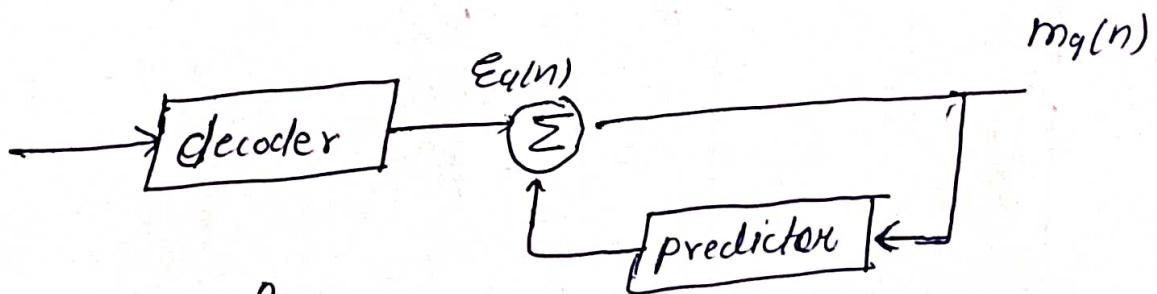
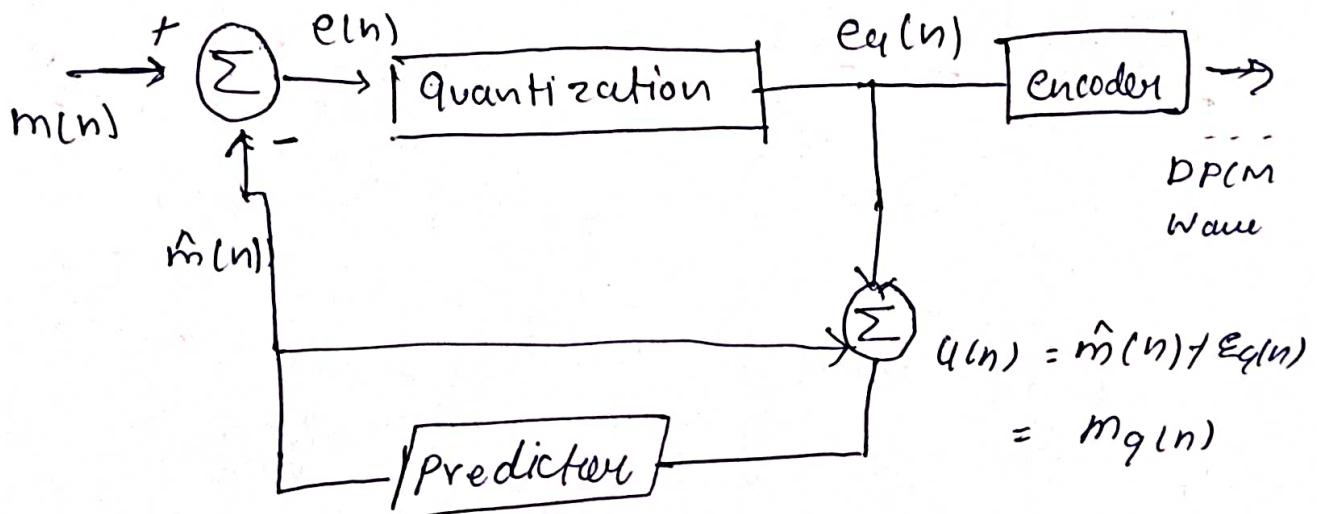
$$e_q(n) = e(n) + q(n)$$

Quantization error

$$\begin{aligned} m_q(n) &= \hat{m}(n) + e_q(n) \\ &= \hat{m}(n) + e(n) + q(n) \end{aligned}$$

Quantized Signal

$$m_q(n) = m(n) + q(n)$$



$$(SNR)_o = \frac{\sigma_m^2}{\sigma_q^2}$$

Error of Prediction

$$= \left(\frac{\sigma_m^2}{\sigma_E^2} \right) \left(\frac{\sigma_E^2}{\sigma_q^2} \right)$$

$$= G_p G_q$$

Predicting gain

Delta Modulator (DM) → why we call delta - because error is bounded by Δ

$x_n > x_{n+1}^{\text{quantized}} \Rightarrow$ binary transmit binary '1'

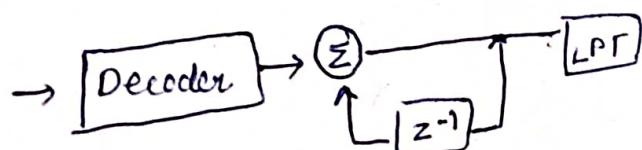
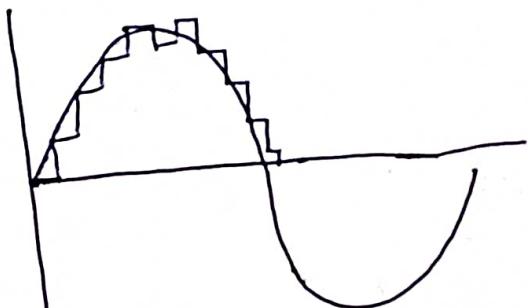
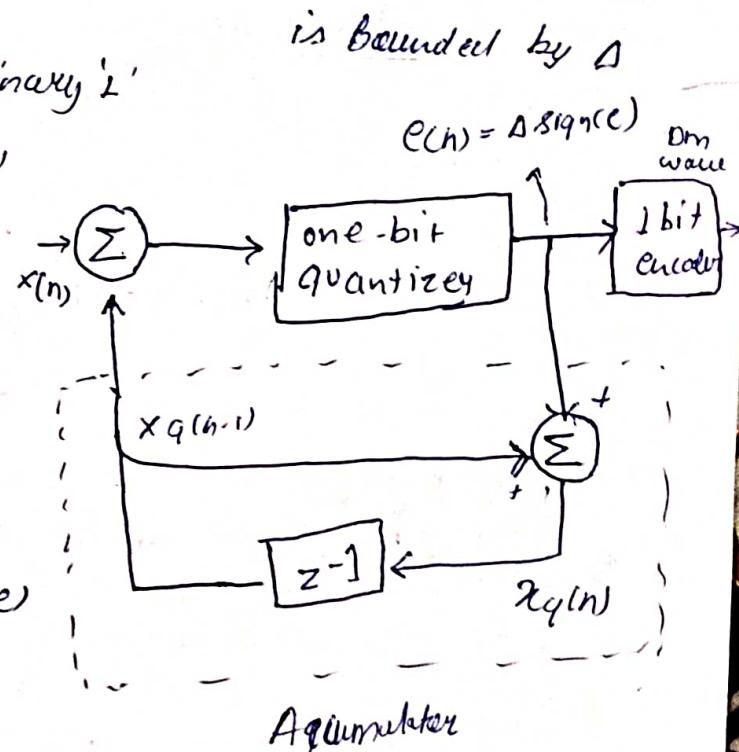
$x_n < x_{n+1} \Rightarrow$ transmit binary '0'

$$e(n) = x(n) - x_q(n-1)$$

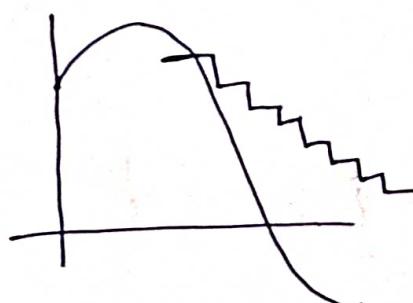
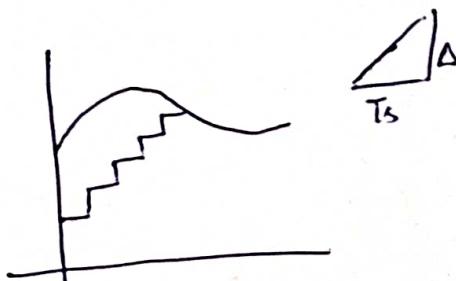
$$= \Delta \operatorname{sign}(e)$$

$$x_q(n) = x(n) + q(n)$$

$$= x_q(n-1) + \Delta \operatorname{sign}(e)$$



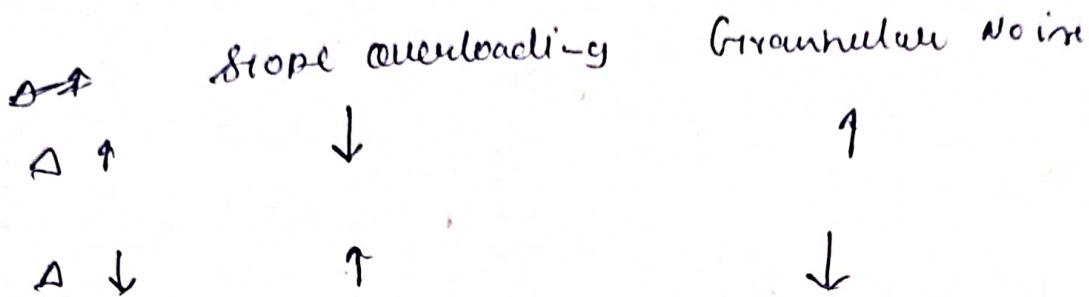
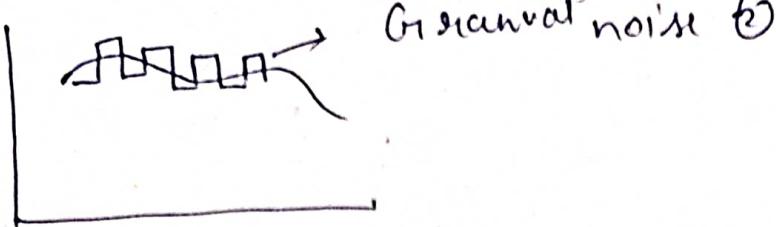
↳ if slope of signal is very less or very more then slope overloading



① Slope Overloading

A.

$$\frac{\Delta}{T_s} \geq \left| \frac{d x(t)}{dt} \right|_{\max}$$



→ So we have to change Δ value with slope → delta-timing.

Adaptive Delta modulation, ADM

$$\Delta_n = \Delta_{n-1} K \hat{e}_n e_n^v \xrightarrow{\substack{\uparrow \\ \leftarrow \\ \uparrow \\ \downarrow}} \Delta_n < \Delta_{\max}$$

e_n = error

$K = \text{constant} \gg 1$

1.5 common choice.

$$e_n = 1 \quad x_n > x_q(n-1)$$

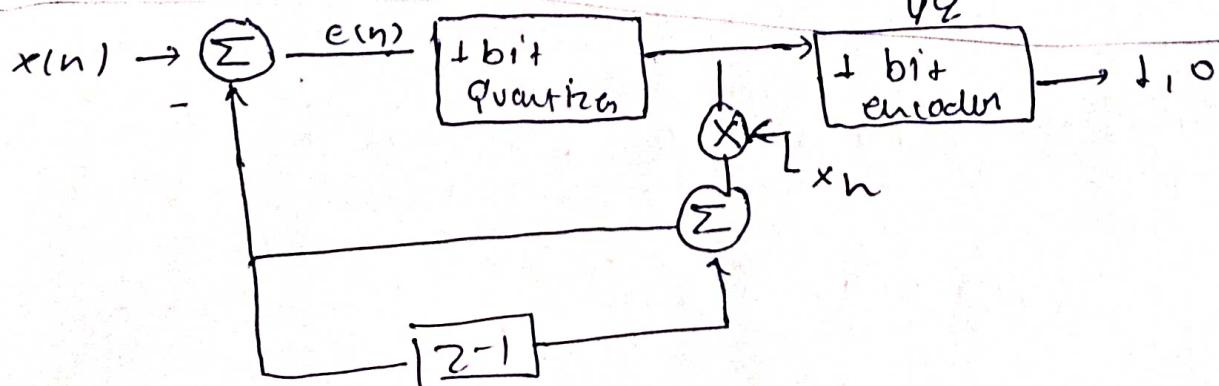
$$e_n = -1 \quad x_n < x_q(n-1)$$

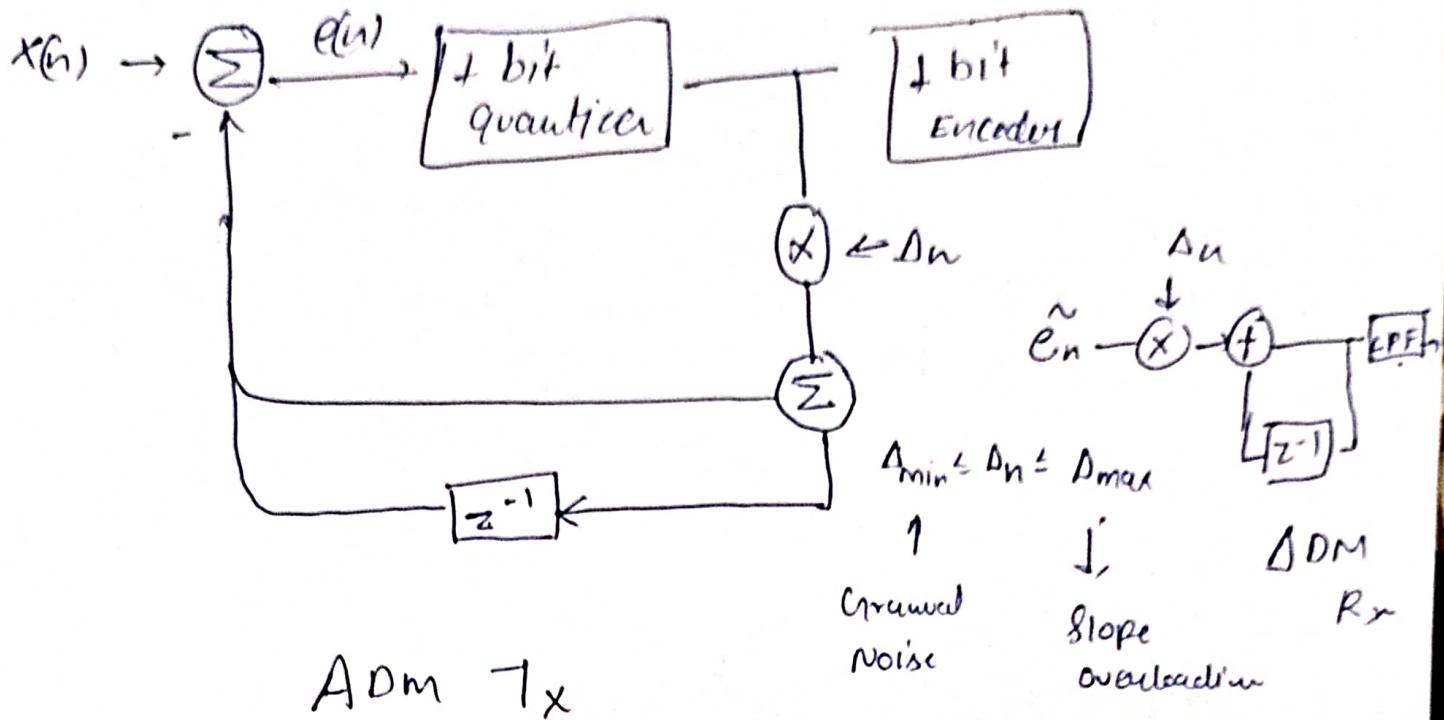
PCM, DM, DPCM, ADM

SQNR + Signal to Quantisation noise Sqnr

$$SQNR = \frac{\overline{x^2}}{\overline{q^2}}$$

$$SQNR_{dB} = 10 \log \left(\frac{\overline{x^2}}{\overline{q^2}} \right)$$





$$|x_{\max}| = |x_{\min}|$$

$n \rightarrow$ no of bits

$$\Delta = \frac{x_{\max} - x_{\min}}{2^n}$$

$$= \frac{2}{2^n} x_{\max}$$

SQNR for sinusoidal Signal

$$\text{Signal Power} = \frac{A^2}{2}$$

$$\text{Quantization noise} = \frac{\Delta^2}{12} \cdot \left(\frac{2A}{2^n} \right)^2 / 12$$

$$\Rightarrow \text{SQNR} = 10 \log \left(\frac{\frac{A^2}{2} \times \frac{12^2}{2^n}}{2 \cdot \frac{4A^2}{2^n} 12^2} \frac{\frac{2^{2n}}{8}}{12^2} \right)$$

$$= 10 \log \left(\frac{A^2}{2} \times \frac{12}{\frac{41^2}{2^{2n}}} \right)$$

$\frac{0.41}{0.2}$

(23)

$$= \log \left(2^{2n} \times \frac{3}{2} \right)$$

\approx Error difference

$$= 10 \log \left(\frac{3}{2} \right) + 2n(\log 2) 10$$

$$= 6n + 18 \text{ dB}$$

Time-Division Multiplexing

$$f_s = 8 \text{ kHz}$$

$$T_s = 125 \text{ us}$$

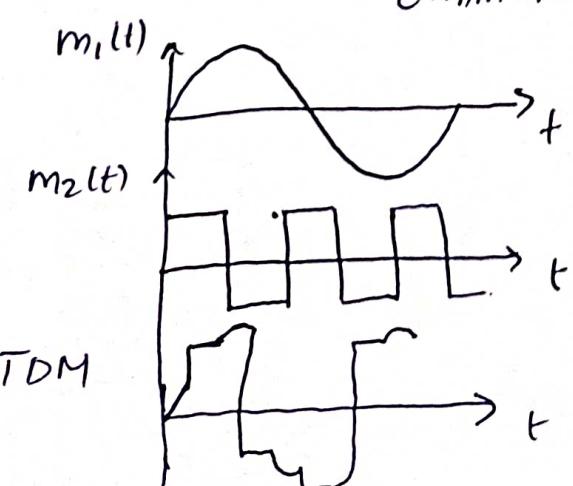
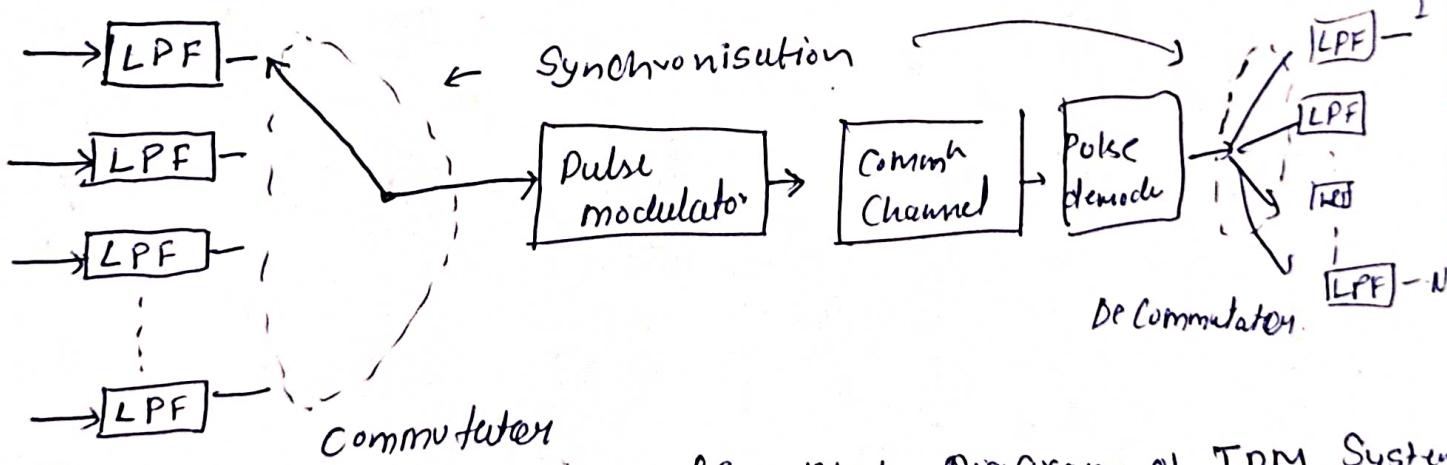
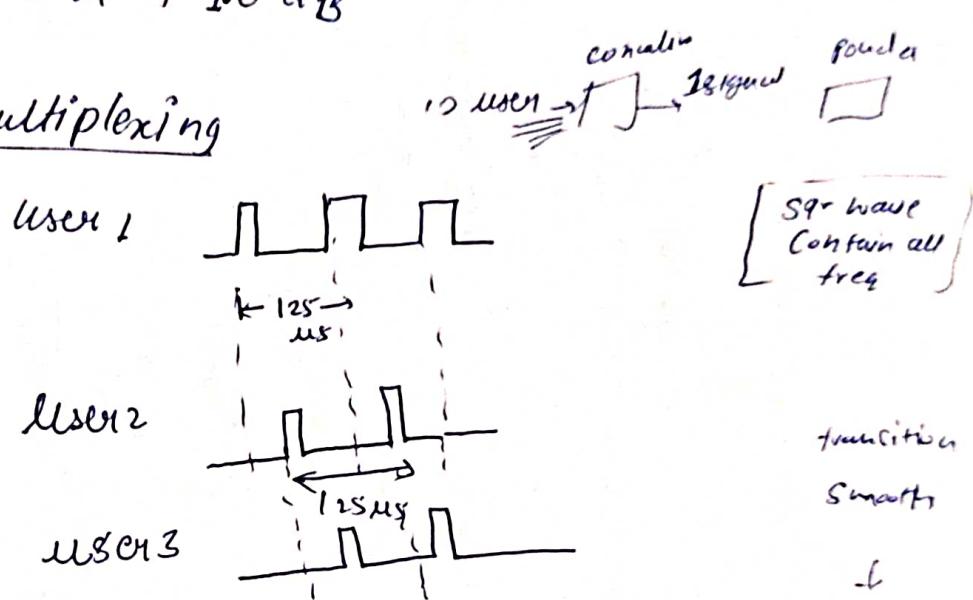
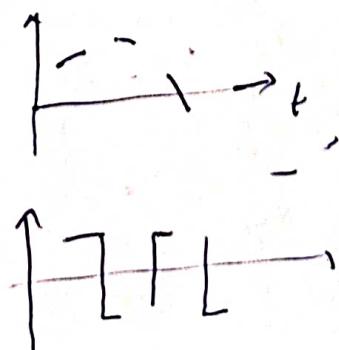


Fig: Block Diagram of TDM System



$$\Delta = \frac{2V}{m} \xrightarrow{\text{Range}} M = \text{No of levels} = 2^n$$

$$\sigma_q^2 = \frac{\Delta^2}{12}$$

$$= \frac{4V^2}{M^2} \times \frac{1}{12}$$

$$= \frac{V^2}{3M^2} = \frac{V^2}{3(2^n)^2}$$

Quantisation
Noise

$$\boxed{\sigma_q^2 = \frac{V^2}{3 \cdot 4^n}}$$

(Assume zero mean)

$$\text{Signal is Random, Signal Power} = \underline{x}^2$$

$$SQR = 10 \log_{10} \frac{\underline{x}^2}{\sigma_q^2}$$

$$= 10 \log \frac{\underline{x}^2}{V^2 / 3 \cdot 4^n}$$

$$= \log \frac{\underline{x}^2}{V^2} + 10 \log_{10} 3 + 10 \log 2^{2n}$$

$$= 10 \log \frac{\underline{x}^2}{V^2} + 6n + 4.8$$

$$V = \sqrt{\frac{1}{x}} \rightarrow 99.99\%$$

$$= 10 \log \frac{\underline{x}^2}{4^2 \sigma_x^2} + 6n + 4.8$$

$$\boxed{SQR = 6n - 7.24}$$