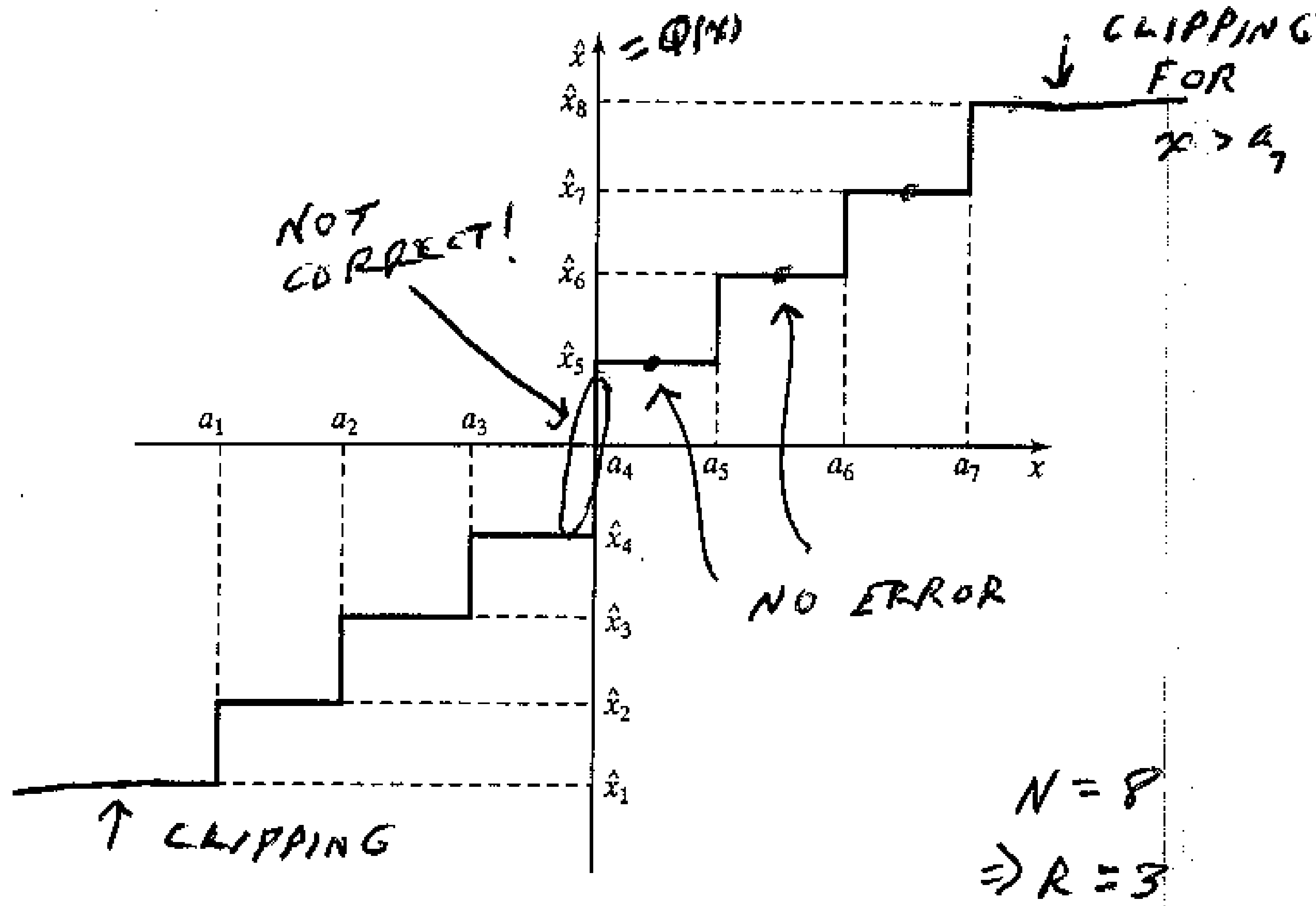


Figure 7.3 Example of an 8-level quantization scheme.

$$\hat{x}_i = Q(x) \qquad \text{FOR} \quad a_{i-1} < x < a_i$$

$x - \hat{x}_i$ IS CALLED <u>QUANTIZATION ERROR</u> OR <u>QUANTIZATION NOISE</u>

IN GENERAL, SINCE x IS RANDOM VARIABLE, WE MEASURE QUANTIZATION NOISE BY ITS POWER OR

$$d(x, \hat{x}) = (x - \hat{x})^2 = (x - Q(x))^2$$

ITS EXPECTED VALUE IS

$$D = E\left[d(x, \hat{x})\right] = E\left((X - Q(X))^2\right)$$

EXAMPLE :

SOURCE $X(t)$ IS STATIONARY GAUSSIAN RANDOM PROCESS WITH $E\{X(t)\} = 0$ AND PSD

$$S_X(f) = \begin{cases} 2 & |f| < 100\ Hz \\ 0 & |f| \geq 100 \end{cases}$$

SAMPLE AT NYQUIST RATE AND USE $N = 8$ LEVEL QUANTIZER,

$$a_i = -60, -40, -20, 0, 20, 40, 60 \qquad i = 1, \ldots, 7$$
$$\hat{x}_i = -70, -50, -30, -10, 10, 30, 50, 70 \qquad i = 1, \ldots, 8$$

$D = ?$

$$D = E\left[(X - Q(X))^2\right]$$

SINCE $X(t)$ IS GAUSSIAN AT ALL TIMES

$$D = \int_{-\infty}^{\infty} (x - Q(x))^2 f_X(x)\, dx$$

WHERE $X \sim N(0, \sigma^2)$

BUT $\sigma^2 = E\left[(X - E[X])^2\right] = E\{X^2\} = R_X(0)$

$$= \int_{-\infty}^{\infty} S_X(f)\, df = \int_{-100}^{100} 2\, df = 400$$

$$\Rightarrow \quad f_X(x) = \frac{1}{\sqrt{2\pi(400)}} e^{-\frac{1}{2(400)}x^2} \qquad -\infty < x < \infty$$

$$D = \sum_{i=1}^{8} \int_{a_{i-1}}^{a_i} (x - \varphi(x))^2 f_X(x)\, dx \qquad a_0 = -\infty, \quad a_8 = \infty$$

SINCE $\varphi(x)$ IS PIECEWISE CONSTANT.

$$D = \int_{-\infty}^{a_1} + \int_{a_1}^{a_2} + \dots + \int_{a_6}^{a_7} + \int_{a_7}^{\infty}$$

$$= \int_{-\infty}^{-60} (x - (-70))^2 f_X(x)\, dx$$

$$+ \int_{-60}^{-40} (x - (-50))^2 f_X(x)\, dx$$

$$+ \dots$$

$$+ \int_{40}^{60} (x - 50)^2 f_X(x)\, dx$$

$$+ \int_{60}^{\infty} (x - 70)^2 f_X(x)\, dx$$

FOR EXAMPLE

$$\int_{40}^{60} (x - 50)^2 f_X(x)\, dx$$

$$= \int_{40}^{60} (x - 50)^2 \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}x^2}\, dx \qquad \sigma^2 = 400$$

$$= \int_{40}^{60} x^2 \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}x^2} dx$$

$$- 100 \int_{40}^{60} x \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}x^2} dx$$

$$+ 2500 \int_{40}^{60} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}x^2} dx$$

$$= -\sigma^2 \int_{40}^{60} \underbrace{x \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}x^2}}_{dv} \underbrace{\left(-\frac{x}{\sigma^2}\right)}_{u} dx$$

$$-100 \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}x^2} (-\sigma^2) \Big|_{40}^{60}$$

$$+ 2500 \left[Q(40/\sigma) - Q(60/\sigma) \right]$$

$$\int u\, dv = uv - \int v\, du$$

INTEGRATION BY PARTS

ULTIMATELY NEED Q FUNCTION
(USE Q.m AND FINISH CALCULATION OF D) D = 33.38

TO CHOOSE A SUITABLE N WE MUST ENSURE SIGNAL POWER >> QUANTIZATION NOISE POWER, WHICH IS

$$SQNR = \frac{E[X^2]}{E[(X - Q(X))^2]} = \frac{E[X^2]}{D}$$

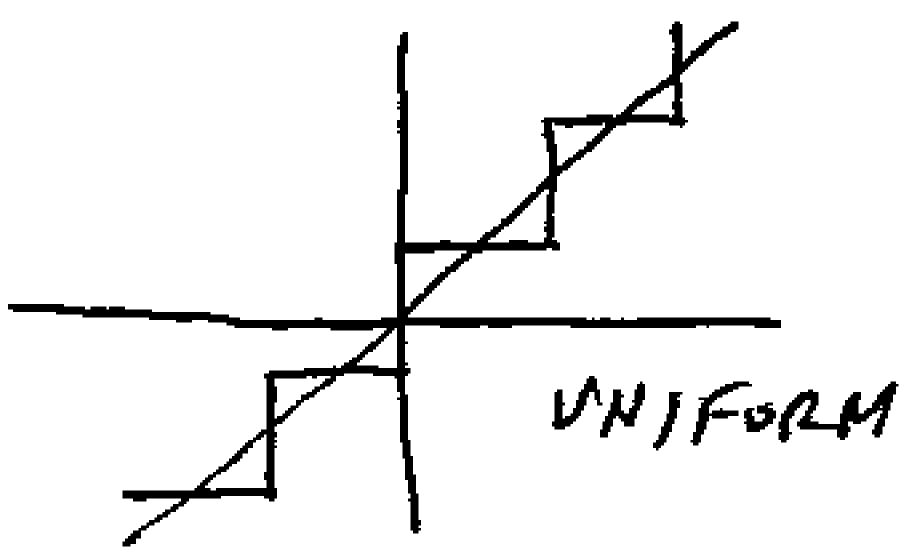
FOR PREVIOUS EXAMPLE $E[X^2] = \sigma^2 = 400$

$\Rightarrow$ SQNR $= \dfrac{\sigma^2}{D} = \dfrac{400}{33.38} = 11.98$

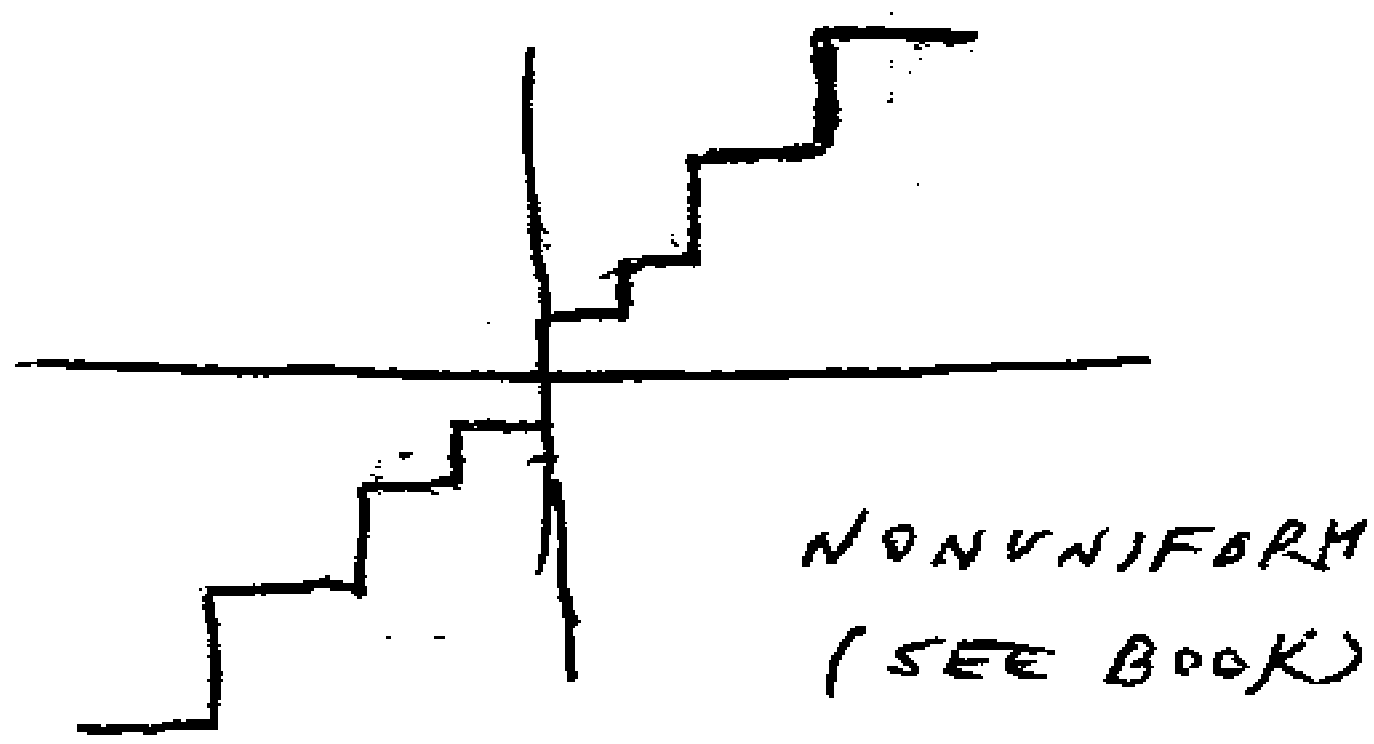
OR $10 \log_{10}$ SQNR $= 10.78$ dB

THIS IS TOO LOW!

UNIFORM QUANTIZERS



AS IN PREVIOUS EXAMPLE



WORKS BETTER IF X IS MORE LIKELY TO BE NEAR $X = 0$ AS OPPOSED TO $X = X_{MAX}$

FOR UNIFORM QUANTIZER:

1) CHOOSE X_{MAX} SO THAT

$|x(t)| \leq X_{MAX}$ ALL t

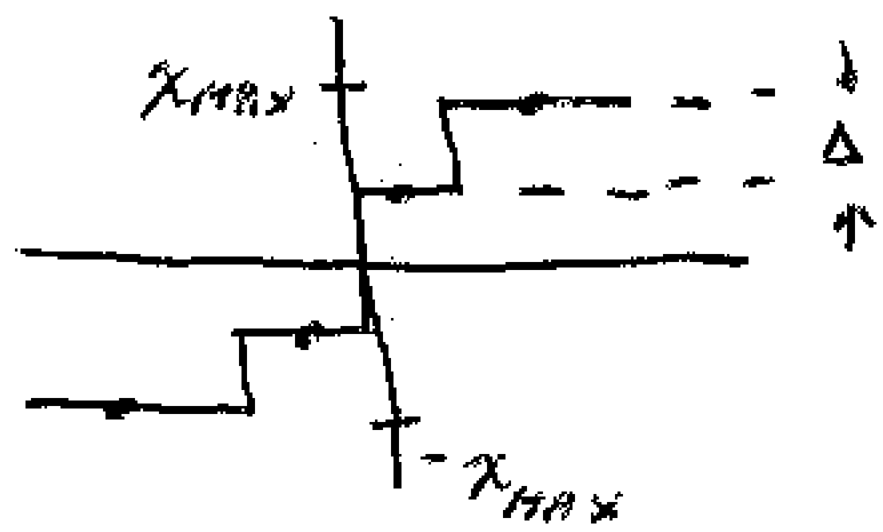
$\Rightarrow$ NO CLIPPING

2) CHOOSE N SO THAT SQNR IS LARGE

TO FIND N ASSUME $N = 2^{\nu}$ AND N IS LARGE. RANGE OF LEVELS IS $[-x_{MAX}, x_{MAX}]$ SO THAT IF LEVELS ARE SEPARATED BY Δ

$$2x_{MAX} = (N-1)\Delta$$

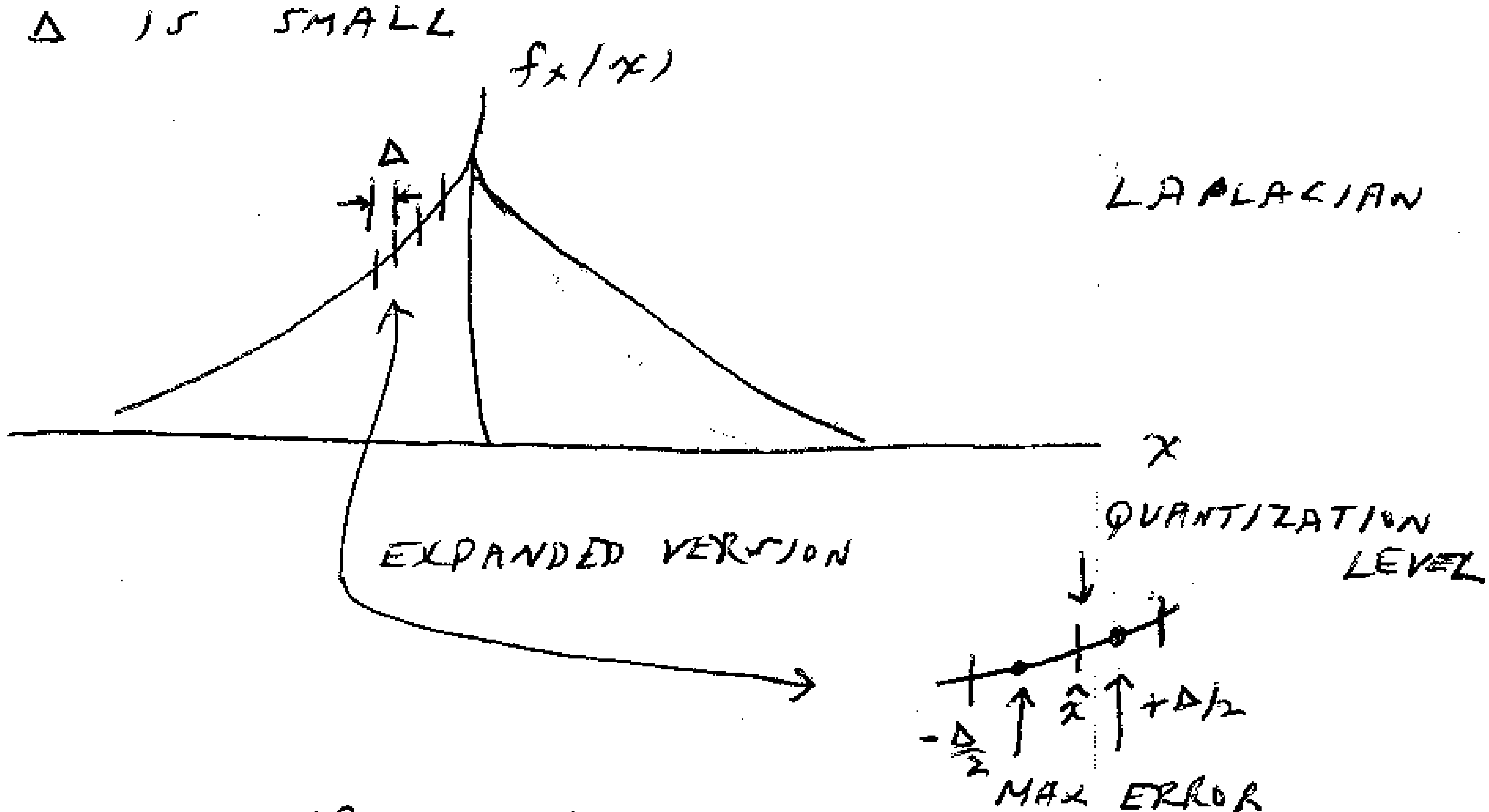
$$\Rightarrow \quad \Delta = \frac{2x_{MAX}}{2^{\nu}-1}$$



$N = 4$

ONCE Δ IS FOUND $\Rightarrow \nu$

TO FIND $D = E\{(x - Q(x))^2\}$ FOR ANY PDF OF X ASSUME N LARGE SO THAT Δ IS SMALL



$-\frac{\Delta}{2} \le \text{ERROR} \le \Delta/2$

AND PDF $\approx$ UNIFORM OVER $[\hat{x} - \frac{\Delta}{2}, \hat{x} + \frac{\Delta}{2}]$

OR ANY Δ LENGTH INTERVAL

$\Rightarrow$ ERROR $= \tilde{x} = x - Q(x)$ HAS PDF

$$f_{\tilde{x}}(\tilde{x}) = \begin{cases} 1/\Delta & -\frac{\Delta}{2} \le \tilde{x} \le \Delta/2 \\ 0 & \text{OTHERWISE} \end{cases}$$

VALID FOR ANY PDF OF X.

$$D = E[(X - Q(X))^2] = E[\tilde{x}^2]$$

$$= \int_{-\Delta/2}^{\Delta/2} \tilde{x}^2 \frac{1}{\Delta} d\tilde{x} = \Delta^2/12$$

IF $E[X^2] = P_X$, THEN

$$SQNR = \frac{P_X}{D} = \frac{P_X}{\Delta^2/12}$$

$$= \frac{P_X}{(2x_{MAX}/2^{\nu}-1)^2/12}$$

$$\approx \frac{12P_X}{(2x_{MAX}/2^{\nu})^2} = \frac{P_X}{x_{MAX}^2} 2^{2\nu-2} \cdot 12$$

IN dB QUANTITIES

$$SQNR = 10\log_{10} \frac{P_X}{x_{MAX}^2} + 6\nu + 4.8$$

NOTE THAT SQNR INCREASES BY 6 dB PER ADDITIONAL BIT.

FOR $X \sim N(0, P_X)$ $x_{MAX} \approx 3\sqrt{P_X}$
AND $\nu = 16$ (AS FOR CDS)

$$SQNR = 10 \log_{10} \frac{P_X}{9 P_X} + 96 + 4.8$$

$$\approx 91.3 \text{ dB}$$

ENCODING

TABLE 7.3 NBC AND GRAY CODES FOR A 16-LEVEL QUANTIZATION

Quantization level	Level order	NBC code	Gray code
$\hat{x}_1$	0	0000	0000
$\hat{x}_2$	1	0001	0010
$\hat{x}_3$	2	0010	0011
$\hat{x}_4$	3	0011	0001
$\hat{x}_5$	4	0100	0101
$\hat{x}_6$	5	0101	0100
$\hat{x}_7$	6	0110	0110
$\hat{x}_8$	7	0111	0111
$\hat{x}_9$	8	1000	1111
$\hat{x}_{10}$	9	1001	1110
$\hat{x}_{11}$	10	1010	1100
$\hat{x}_{12}$	11	1011	1101
$\hat{x}_{13}$	12	1100	1001
$\hat{x}_{14}$	13	1101	1000
$\hat{x}_{15}$	14	1110	1010
$\hat{x}_{16}$	15	1111	1011

1 BIT CHANGE ⇒ 8 LEVEL CHANGE

ONLY 1 BIT CHANGES BETWEEN LEVELS

NBC = NATURAL BINARY ENCODING

GRAY CODE IS PREFERRED SINCE IF A BIT IS IN ERROR AT RECEIVER THE DECODER YIELDS ONE LEVEL CHANGE ONLY.

WAVEFORM CODING

TAKE ANALOG WAVEFORM AS INPUT AND PRODUCE BITS AS OUTPUT.

PULSE CODE MODULATION (ACTUALLY JUST AN A/D CONVERTOR)

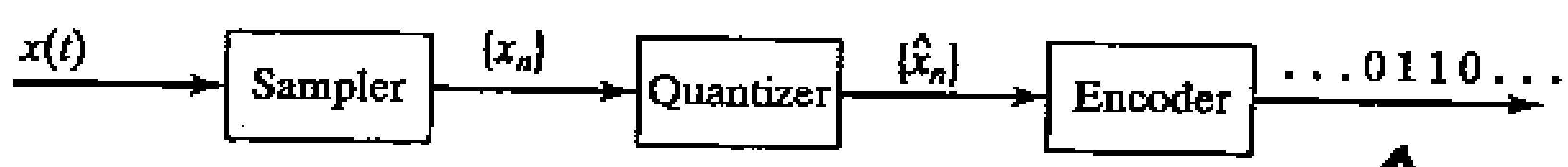


Figure 7.7 Block diagram of a PCM system.

BLOCKS OF ν BITS PER SAMPLE

USED IN T1 CARRIER FOR MULTIPLE VOICE CHANNELS.

REQUIRES MORE BANDWIDTH THAN 8 KHz PER VOICE CHANNEL. TO SEE THIS:

FOR NYQUIST SAMPLING WE HAVE

BPS = BITS/SEC = (SAMPLES/SEC) × (BITS/SAMPLE)

$$= f_s \nu = 2W\nu \quad \text{(OUTPUT OF ENCODER)}$$

BUT TO TRANSMIT R BPS WE WILL SEE LATER THAT BANDWIDTH NEEDED IS

$$BW = R/2 \qquad \text{(ABSOLUTE MINIMUM)}$$

$$\Rightarrow \quad BW = \frac{2W\nu}{2} = \nu W \ \text{Hz}$$

AS BITS USED INCREASES, SO DOES BANDWIDTH. IN T1 CARRIER $\nu = 8$ AND $W = 4000$ AND $BW = R$

$$\Rightarrow \quad BW = R = 2W\nu = 2(4000)8 = 64{,}000 \ \text{Hz}$$

GAIN NOISE IMMUNITY FOR INCREASED BANDWIDTH USED.

DIFFERENTIAL PCM

SOME SIGNALS ARE HIGHLY CORRELATED FOR TWO SUCCESSIVE SAMPLES. IF PERFECTLY CORRELATED, NO NEED TO TRANSMIT BOTH SAMPLES.

$\rho = 1$

USUALLY HOWEVER IT IS MORE LIKE

CONSIDER AUTOREGRESSIVE RANDOM PROCESS $X_n = a X_{n-1} + U_n$

WHITE GAUSSIAN NOISE, $VAR = \sigma_U^2$

AUTOCORRELATION SEQUENCE

$$R_X[k] = \frac{\sigma_U^2}{1-a^2} (-a)^{|k|}$$

INSTEAD OF SENDING X_n WE COULD TRANSMIT $X_n - a X_{n-1}$ (IF a WERE KNOWN)

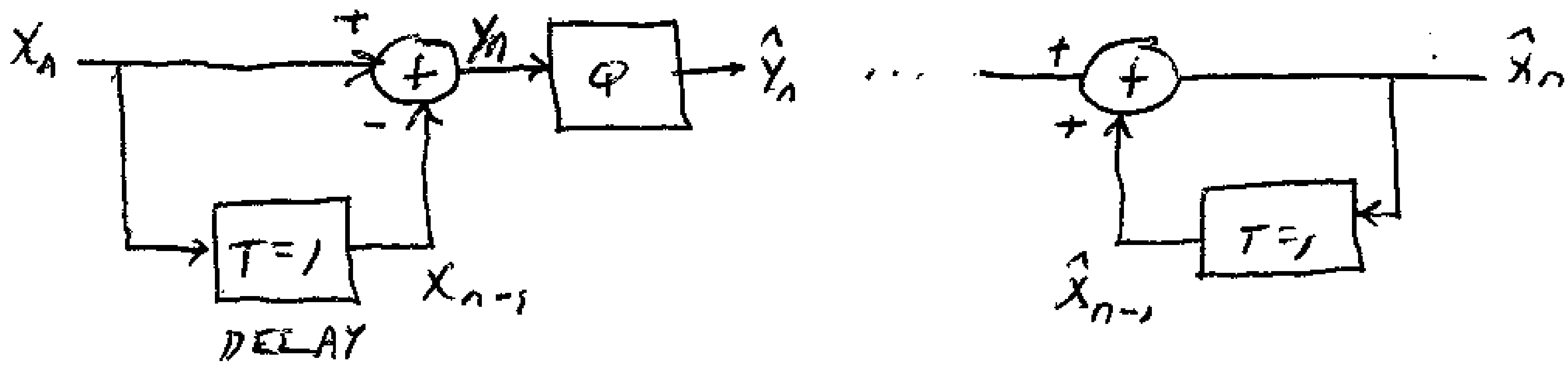
POWER IN $X_n - a X_{n-1} \Rightarrow \sigma_U^2$

POWER IN $X_n \Rightarrow R_X(0) = \frac{\sigma_U^2}{1-a^2}$

HAVE REDUCED POWER BY FACTOR OF $R_X(0)/\sigma_U^2 = 1/1-a^2 > 1 \Rightarrow$ CAN USE LESS LEVELS IN QUANTIZER $\Rightarrow$ LESS BITS NEEDED

SINCE a IS UNKNOWN, A SIMILAR APPROACH IS DIFFERENTIAL PCM

TRANSMIT $y_n = x_n - x_{n-1}$ RECEIVE $x_n = y_n + x_{n-1}$



DPCM ENCODER DECODER

NOTE THAT $\hat{y}_n \neq y_n$ DUE TO QUANTIZATION NOISE, $\hat{y}_n = y_n + \epsilon_n$. AT DECODER

$$\hat{x}_n = \hat{y}_n + \hat{x}_{n-1}$$

$$\hat{x}_0 = \hat{y}_0 + 0 \qquad \text{START AT } n=0$$

$$\hat{x}_1 = \hat{y}_1 + \hat{x}_0$$

$$= \hat{y}_1 + \hat{y}_0$$

$$\hat{x}_2 = \hat{y}_2 + \hat{x}_1 = \hat{y}_2 + \hat{y}_1 + \hat{y}_0$$

$$= y_2 + y_1 + y_0 + \epsilon_2 + \epsilon_1 + \epsilon_0$$

$$= x_2 - x_1 + x_1 - x_0 + x_0 - \cancel{x_{-1}}^{0} + \epsilon_2 + \epsilon_1 + \epsilon_0$$

$$= x_2 + \underbrace{\epsilon_0 + \epsilon_1 + \epsilon_2}_{}$$

ACCUMULATION
OF QUANTIZATION ERROR

HOW DO WE AVOID THIS? USE SAME DECODER (SUMMER) BUT CONVERT ϵ_n TO $u_n - u_{n-1}$ SOMEHOW.

WHEN SUMMED $\Rightarrow (u_2-u_1)+(u_1-u_0)+(u_0-u_{-1})$
$= u_2$

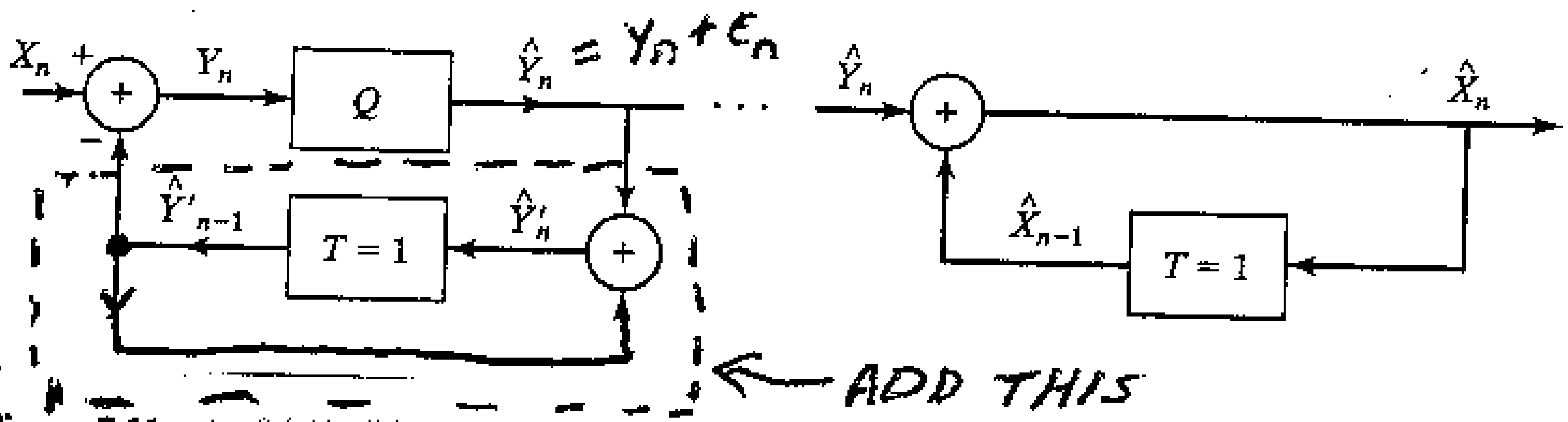
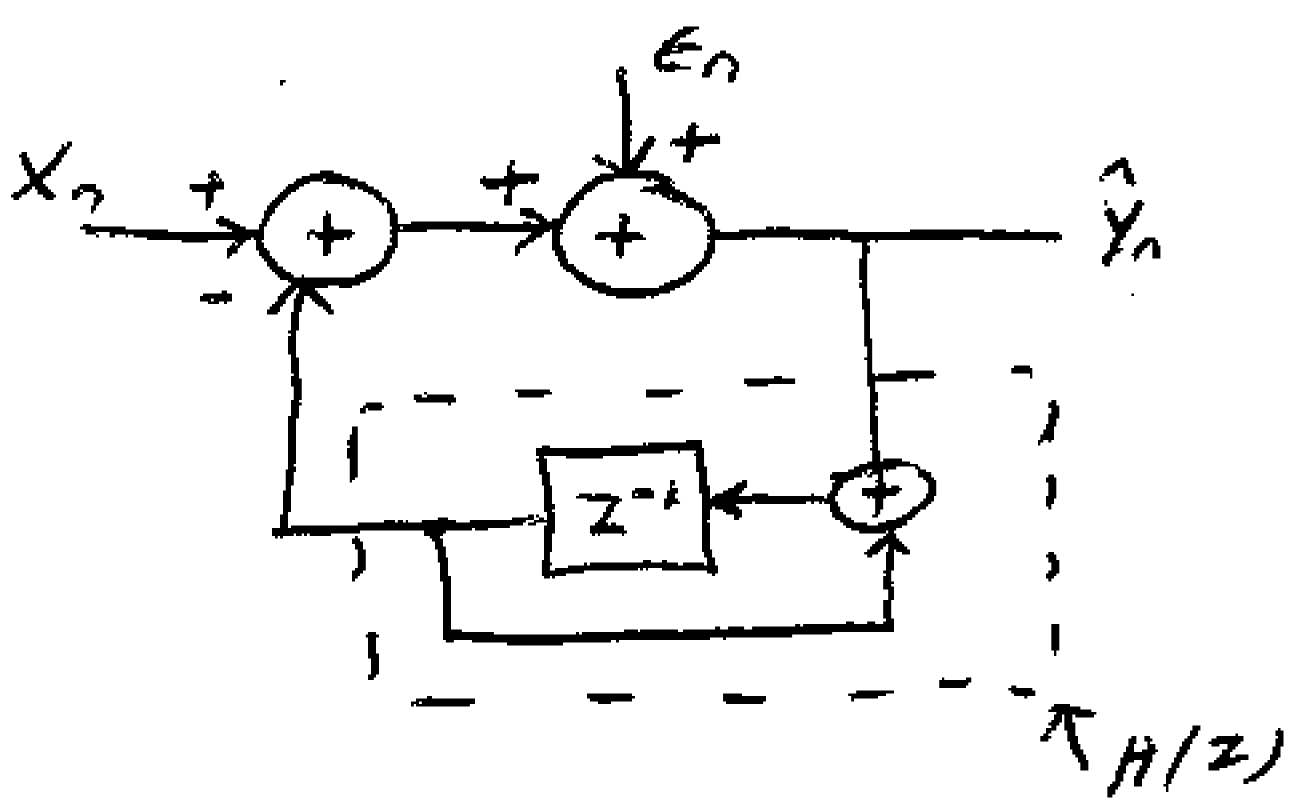
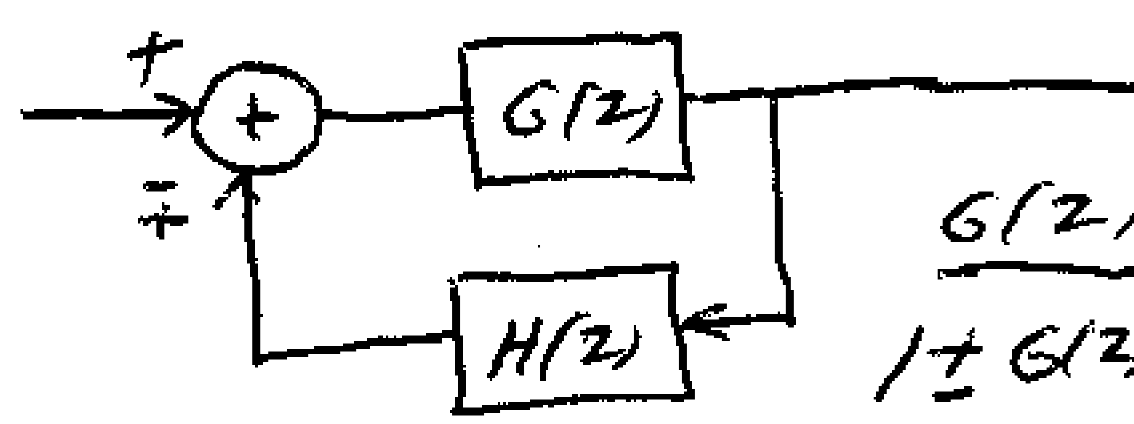


Figure 7.11 A simple DPCM encoder and decoder.

WHAT IS $\hat{Y}_n$ NOW? USE Z-TRANSFORMS



SYSTEM IS LINEAR WITH TWO INPUTS X_n AND ϵ_n

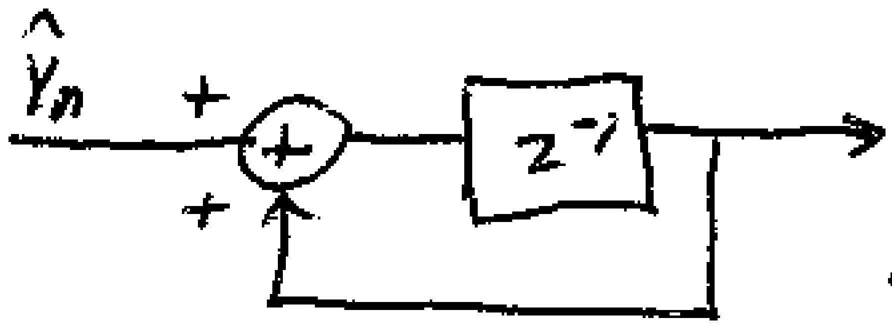


$$\frac{G(z)}{1 \pm G(z)H(z)}$$

TRANSFER FUNCTION

USING SUPERPOSITION

1) OUTPUT DUE TO X_n (SET $\epsilon_n = 0$)

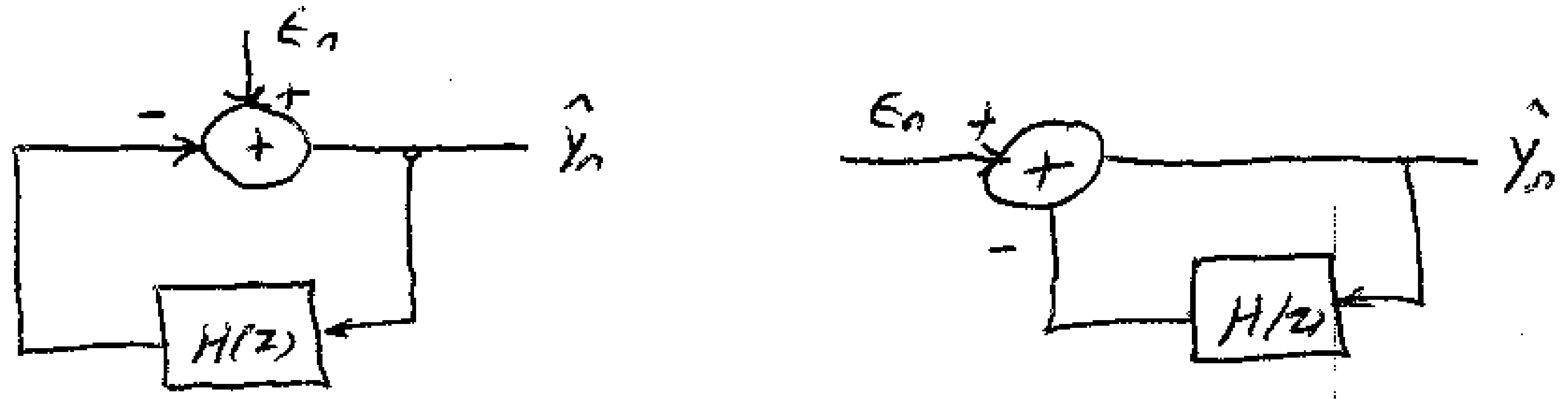


$$H(z) = \frac{z^{-1}}{1-z^{-1}}$$

$$\Rightarrow \frac{1}{1+H(z)} = \frac{1}{1+\frac{z^{-1}}{1-z^{-1}}} = \frac{1-z^{-1}}{1-z^{-1}+z^{-1}} = 1-z^{-1}$$

$$\Rightarrow \hat{Y}_n = X_n - X_{n-1}$$

2) OUTPUT DUE TO ϵ_n



$$\Rightarrow \quad \frac{1}{1+H(z)} = 1 - z^{-1} \quad \Rightarrow \hat{y}_n = \epsilon_n - \epsilon_{n-1}$$

$$\therefore \quad \hat{y}_n = (x_n - x_{n-1}) + (\epsilon_n - \epsilon_{n-1})$$

AFTER DECODING

$\hat{x}_n = x_n + \epsilon_n$ NO ACCUMULATION OF QUANTIZATION NOISE!

A SIMILAR SCHEME USES A <u>ONE BIT</u> QUANTIZER BUT INCREASES SAMPLING RATE SO $x_n - x_{n-1}$ IS SMALL. CALLED <u>DELTA MODULATION</u> (SEE BOOK). EASIER IMPLEMENTATION IN HARDWARE.

<u>ANALYSIS - SYNTHESIS TECHNIQUES</u>

MODELS WAVEFORM USING SET OF PARAMETERS - TRANSMIT PARAMETERS ONLY.

<u>EXAMPLE</u>: $A\cos(2\pi f_0 t + \phi)$

TRANSMIT A, f_0, ϕ ONLY.

USED FOR SPEECH TRANSMISSION. –

LINEAR PREDICTIVE CODING (LPC)

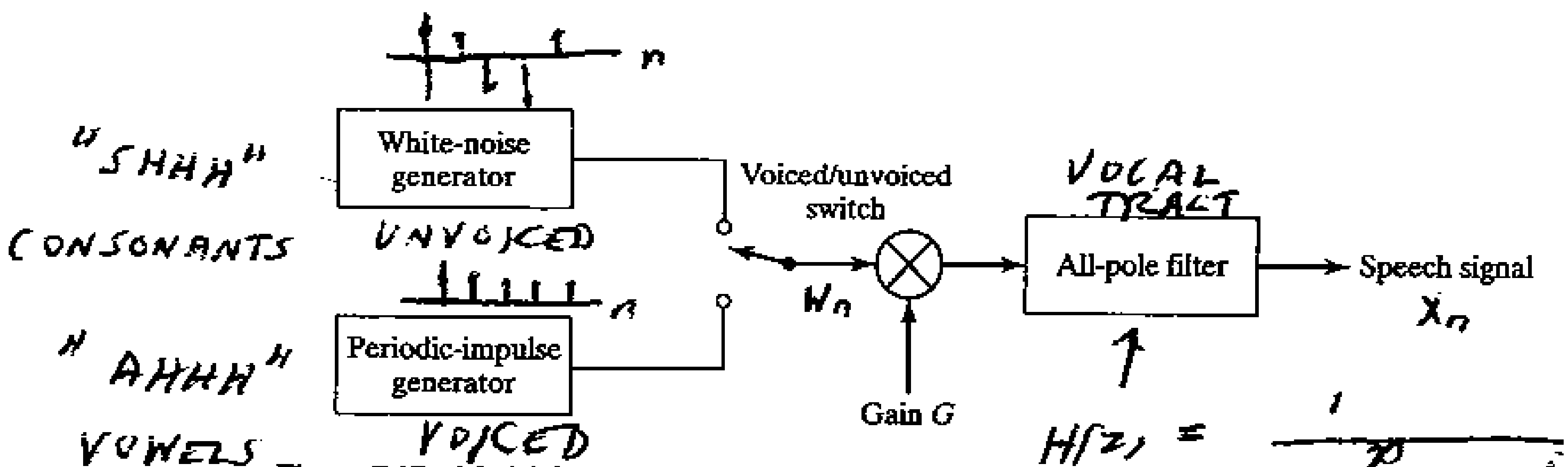


Figure 7.17 Model for speech generation mechanism.

$$H(z) = \frac{1}{1 - \sum_{i=1}^{p} a_i z^{-i}}$$

THIS MODEL VALID OVER DURATION OF SOUND $\approx$ 20 ms (SPEECH IS LOCALLY STATIONARY)

NOTE: $p = 1 \Rightarrow X_n = a_1 X_{n-1} + \underbrace{G W_n}_{u_n}$

LOOK FAMILIAR? AR(1) MODEL

HERE u_n IS EITHER WHITE NOISE OR IMPULSE TRAIN.

NEED TO ESTIMATE $\{a_1, a_2, \ldots, a_p, G\}$

USUALLY $f_s = 8000$ SAMPLES/SEC $\Rightarrow$ $8000 \times 20 \times 10^{-3} = 160$ SAMPLES TO USE FOR ESTIMATION.

EXAMPLE: u_n IS WHITE NOISE, VARIANCE $= \sigma_u^2$

$p = 1$

$$R_x[k] = \frac{\sigma_v^2}{1-a_1^2} a_1^{|k|}$$

$$\frac{R_x[1]}{R_x[0]} = a_1 \Rightarrow \text{NEED TO ESTIMATE } R_x[0],\ R_x[1]$$

MORE GENERALLY, LINEAR PREDICTION EQUATIONS WHEN SOLVED FOR AR(p) RANDOM PROCESS YIELD $\{a_1, a_2, \ldots, a_p, \sigma_v^2\}$

$$\hat{x}_n = \sum_{k=1}^{p} a_k x_{n-k} \qquad \text{LINEAR PREDICTOR}$$

TO FIND a_k's MINIMIZE MEAN SQUARE ERROR
$E\{(x_n - \hat{x}_n)^2\}$

$$\approx \frac{1}{N} \sum_{n=1}^{N} (x_n - \hat{x}_n)^2 \qquad \text{USES SPEECH SAMPLES}$$

LET $\mathcal{E}_p = \frac{1}{N} \sum_{n=1}^{N} \underbrace{(x_n - \hat{x}_n)}_{e_n \text{ - PREDICTION ERROR}}^2$

AND MINIMIZE OVER a_k's USING SPEECH DATA $x_1, x_2, \ldots, x_N$

$$\mathcal{E}_p = \frac{1}{N} \sum_{n=1}^{N} \left(x_n - \sum_{k=1}^{p} a_k x_{n-k}\right)^2$$

TO SIMPLIFY MATTERS LET x_n BE DEFINED AS $x_n = 0$ FOR $n \leq 0$, $n \geq N+1$

$$\varepsilon_p = \frac{1}{N}\sum_{n=-\infty}^{\infty}\left(x_n - \sum_{k=1}^{p} a_k x_{n-k}\right)^2$$

$$\frac{\partial \varepsilon_p}{\partial a_i} = \frac{1}{N}\sum_{n=-\infty}^{\infty} -2\left(x_n - \sum_{k=1}^{p} a_k x_{n-k}\right) x_{n-i} = 0 \qquad i = 1, 2, \ldots, p$$

$$\frac{1}{N}\sum_{n=-\infty}^{\infty} x_n x_{n-i} = \frac{1}{N}\sum_{n=-\infty}^{\infty}\sum_{k=1}^{p} a_k x_{n-k} x_{n-i}$$

$$= \sum_{k=1}^{p} a_k \left[\frac{1}{N}\sum_{n=-\infty}^{\infty} x_{n-i} x_{n-k}\right]$$

LET $\hat{R}_i = \frac{1}{N}\sum_{n=-\infty}^{\infty} x_n x_{n-i}$

$$\hat{R}_i = \sum_{k=1}^{p} a_k \underbrace{\left[\frac{1}{N}\sum_{n=-\infty}^{\infty} x_{n-i} x_{n-k}\right]}$$

LET $m = n-i$ REPLACE n

$$\frac{1}{N}\sum_{m=-\infty}^{\infty} x_m x_{m+i-k} = \hat{R}_{i-k}$$

$$\therefore \quad \hat{R}_i = \sum_{k=1}^{p} a_k \hat{R}_{i-k} \qquad i = 1, 2, \ldots, p$$

FOR $p = 3$

$$\underbrace{\begin{bmatrix} \hat{R}_0 & \hat{R}_{-1} & \hat{R}_{-2} \\ \hat{R}_1 & \hat{R}_0 & \hat{R}_{-1} \\ \hat{R}_2 & \hat{R}_1 & \hat{R}_0 \end{bmatrix}}_{\hat{\underline{R}}} \underbrace{\begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}}_{\underline{a}} = \underbrace{\begin{bmatrix} \hat{R}_1 \\ \hat{R}_2 \\ \hat{R}_3 \end{bmatrix}}_{\hat{\underline{r}}}$$

LINEAR PREDICTION EQUATIONS

SHOW THAT $\hat{R}_{-i} = \hat{R}_i$

$\hat{\underline{R}}$ IS SYMMETRIC TOEPLITZ MATRIX

FOR $p=1$ $\quad a_1 = \hat{R}_1 / \hat{R}_0$

WHAT IS $\hat{R}_i$ FOR $i = 0, 1, \ldots, p$?

$$\hat{R}_i = \frac{1}{N} \sum_{n=-\infty}^{\infty} x_n \, x_{n-i} \qquad x_n = 0 \quad \begin{matrix} n \geq N+1 \\ n \leq 0 \end{matrix}$$

≥ 1 & $\leq N$

$$= \frac{1}{N} \sum_{n=1}^{N} x_n \, \underbrace{x_{n-i}}_{\geq 1 \ \& \ \leq N}$$

FOR $i \geq 0$ INDEX IS $\leq N$,

$n - i \geq 1 \Rightarrow n \geq i+1$

$$\hat{R}_i = \frac{1}{N} \sum_{n=i+1}^{N} x_n \, \underbrace{x_{n-i}}_{m} = \frac{1}{N} \sum_{m=1}^{N-i} x_{m+i} \, x_m$$

$$\Rightarrow \hat{R}_i = \frac{1}{N} \sum_{n=1}^{N-i} x_n \, x_{n+i} \qquad i = 0, 1, \ldots, p \ll N$$

THIS IS USUAL AUTOCORRELATION ESTIMATE (ALTHOUGH DIVIDED BY N, NOT $N-i$)

LASTLY, TO ESTIMATE G:

$$x_n = \sum_{k=1}^{p} a_k \, x_{n-k} + G w_n \qquad E[w_n^2] = 1$$

$$G^2 \underbrace{E[w_n^2]}_{1} = E\left[\left(x_n - \sum_{k=1}^{p} a_k \, x_{n-k} \right)^2 \right]$$

ESTIMATED PARAMETERS

$$\approx \frac{1}{N}\sum_{n=1}^{N}\left(x_n - \sum_{k=1}^{p}\hat{a}_k x_{n-k}\right)^2$$

$$= \frac{1}{N}\sum_{n=1}^{N}\left(x_n - \sum_{k=1}^{p}\hat{a}_k x_{n-k}\right)\left[x_n - \sum_{i=1}^{p}\hat{a}_i x_{n-i}\right]$$

$$= \frac{1}{N}\sum_{n=1}^{N}\left(x_n - \sum_{k=1}^{p}\hat{a}_k x_{n-k}\right)x_n$$

$$- \frac{1}{N}\sum_{i=1}^{p}\hat{a}_i \underbrace{\sum_{n=1}^{N}\left(x_n - \sum_{k=1}^{p}\hat{a}_k x_{n-k}\right)x_{n-i}}_{=0 \quad i=1,2,\dots,p}$$

WHY?

$$= \frac{1}{N}\sum_{n=1}^{N}x_n^2 - \sum_{k=1}^{p}\hat{a}_k \frac{1}{N}\sum_{n=1}^{N}x_n x_{n-k}$$

$$= \hat{R}_0 - \sum_{k=1}^{p}\hat{a}_k \hat{R}_k$$

THUS, $G = \sqrt{\hat{R}_0 - \sum_{k=1}^{p}\hat{a}_k \hat{R}_k}$

NOTES:

1) FOR W_n = IMPULSE TRAIN WE GET SAME RESULTS FOR ESTIMATES, NEED TO ESTIMATE ALSO PITCH PERIOD, P.

2) COMPRESSED TO 2400 BPS BY REPRESENTING $\{a_1, a_2, \dots, a_p, G, P\}$ USING BITS FOR $p=10$

CALLED LPC-10

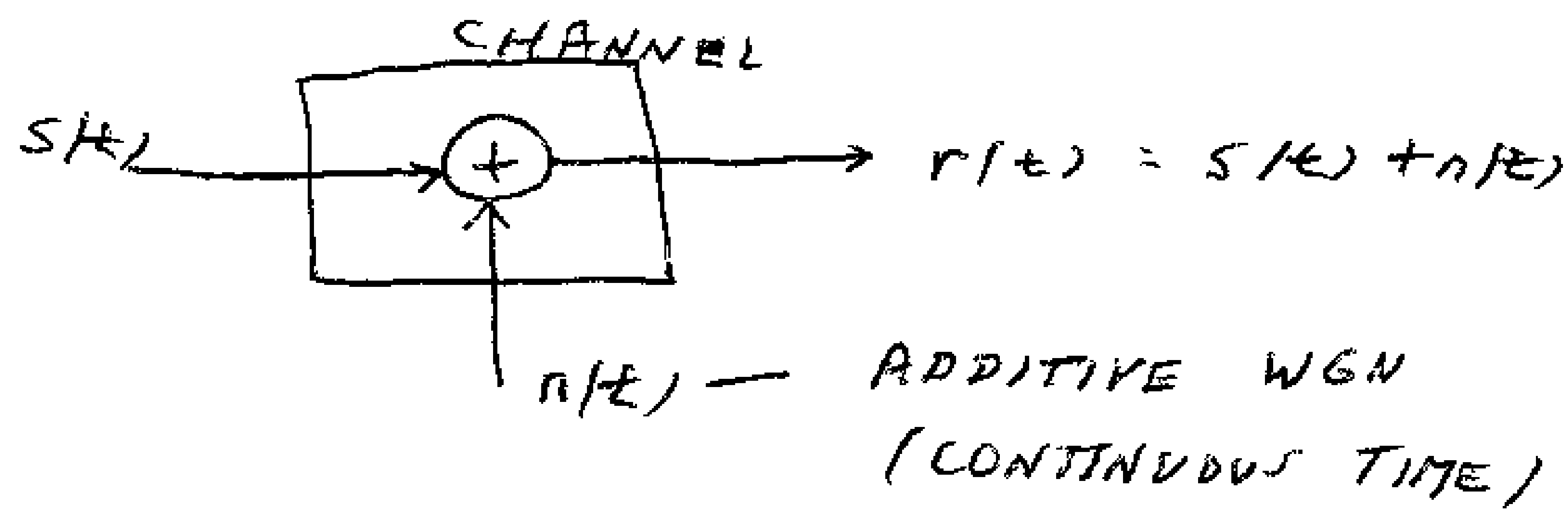
3) VOICE CAN BE ENCRYPTED EASILY - "SECURE" LINES

READ 7.6, 7.7 - CDS AND JPEG

CHAPTER 8 - BASEBAND CHANNELS AND DIGITAL MODULATION (8.1 - 8.5)

BASEBAND CHANNEL ALLOWS TRANSMISSION NEAR $f = 0$ (DC) ONLY. EXAMPLE IS TWISTED PAIR OF WIRES.

WILL CONSIDER ONLY ONE SHOT TRANSMISSION - SINGLE WAVEFORM (FOR NOW) AND CHANNEL DOES NOT DISTORT WAVEFORM



GEOMETRIC REPRESENTATION OF WAVEFORMS

DIGITAL MODULATION - TRANSMIT A DIFFERENT WAVEFORM FOR EACH "MESSAGE"