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Speech Coding

# **SAMPLING AND QUANTIZATION**




# Outline

- Introduction
  - Sampling
  - Scalar Quantization
    - Quantization Error
    - Uniform Quantizer
    - Optimum Quantizer
    - Logarithmic Quantizer
    - Adaptive Quantizer
    - Differential Quantizer
- 



# Introduction

- The digital conversion process can be split into sampling, which discretizes the continuous time, and quantization, which reduces the infinite range of the sampled amplitudes to a finite set of possibilities.
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# Sampling

- The sampled waveform can be represented by

$$s(n) = s_a(nT) \quad -\infty < n < \infty$$

- The sampling theorem states that if a signal  $s_a(t)$  has a band-limited Fourier transform  $S_a(j\omega)$  given by

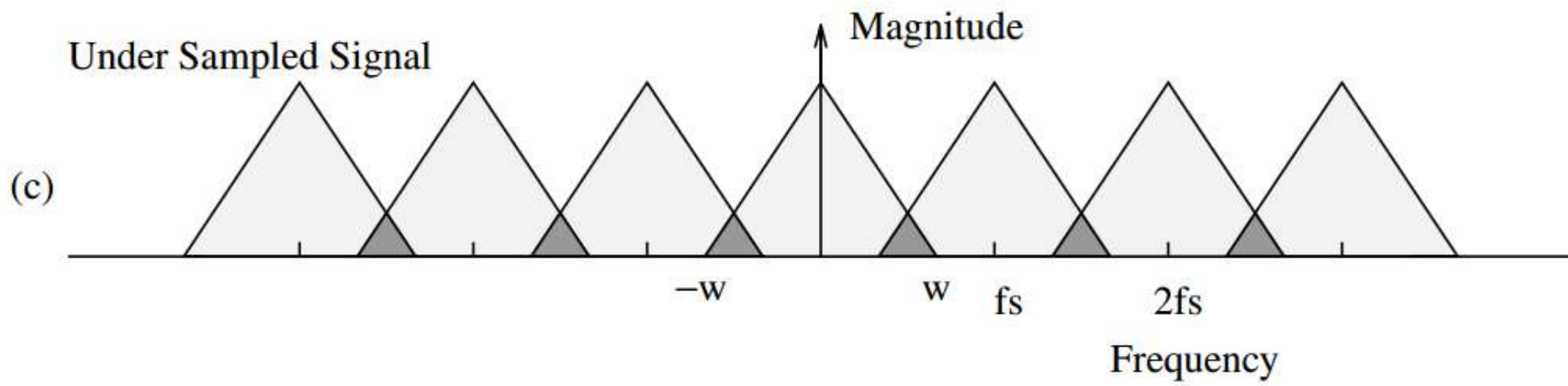
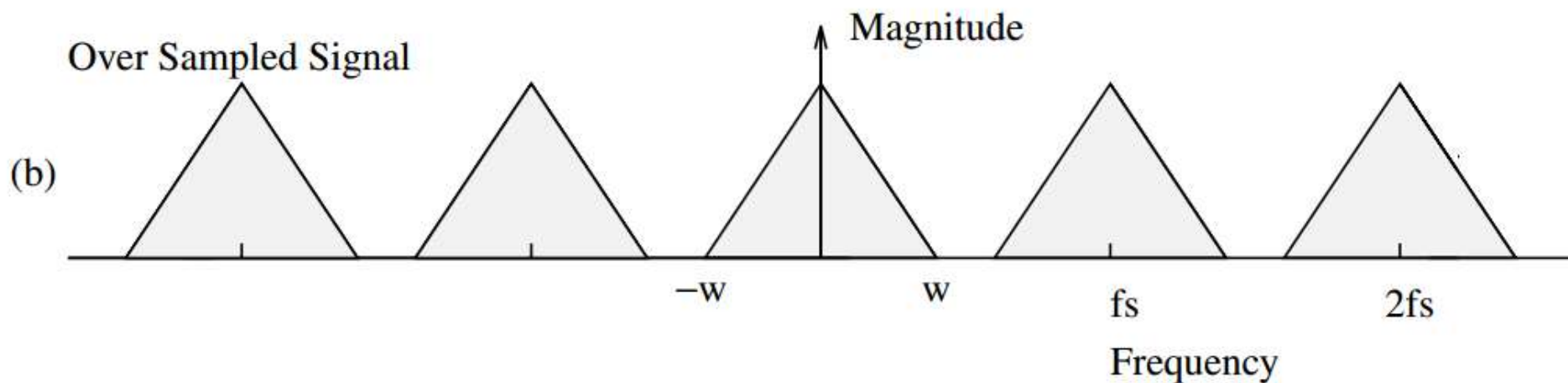
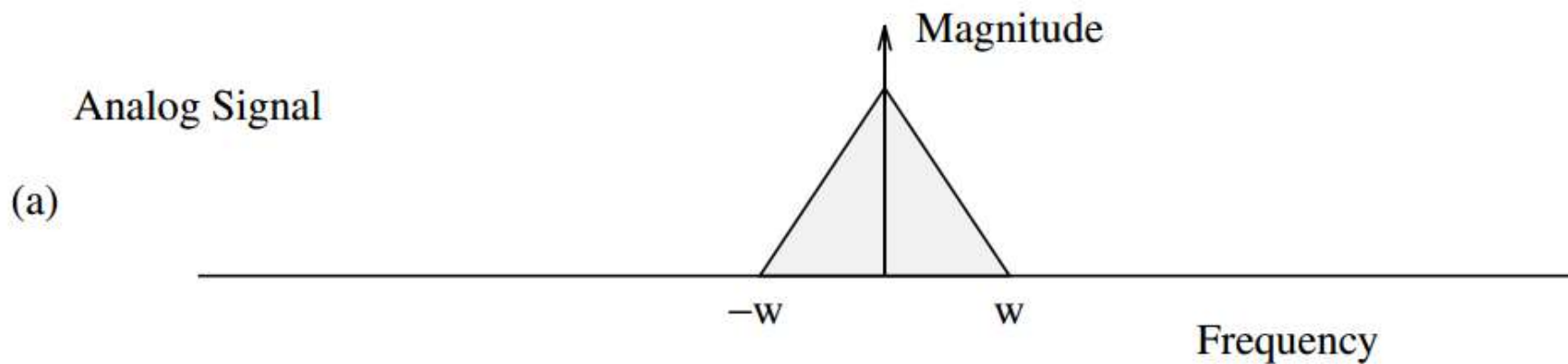
$$S_a(j\omega) = \int_{-\infty}^{\infty} s_a(t)e^{-j\omega t} dt$$

- such that  $S_a(j\omega)=0$  for  $|\omega| \geq 2\pi W$  then the analogue signal can be reconstructed from its sampled version if  $T \leq 1/2W$ .  $W$  is called the Nyquist frequency.

# Sampling Contd...

- The Fourier transform of the sampled signal is evaluated at multiples of the sampling frequency which forms the relationship

$$S(e^{j\omega T}) = \frac{1}{T} \sum_{n=-\infty}^{\infty} S_a(j\omega + j2\pi n/T)$$



# Sampling Contd...

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# Sampling Contd...

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$$S(e^{j\omega T}) = \frac{1}{T} \sum_{n=-\infty}^{\infty} S_a(j\omega + j2\pi n/T)$$

- Fourier transform of the sampled sequence is proportional to the Fourier transform of the analogue signal in the base band as follows

$$S(e^{j\omega T}) = \frac{1}{T} S_a(j\omega) \quad |\omega| < \frac{\pi}{T}$$


# Sampling Contd...

- The original analogue signal can be obtained from the sampled sequence using interpolation given by

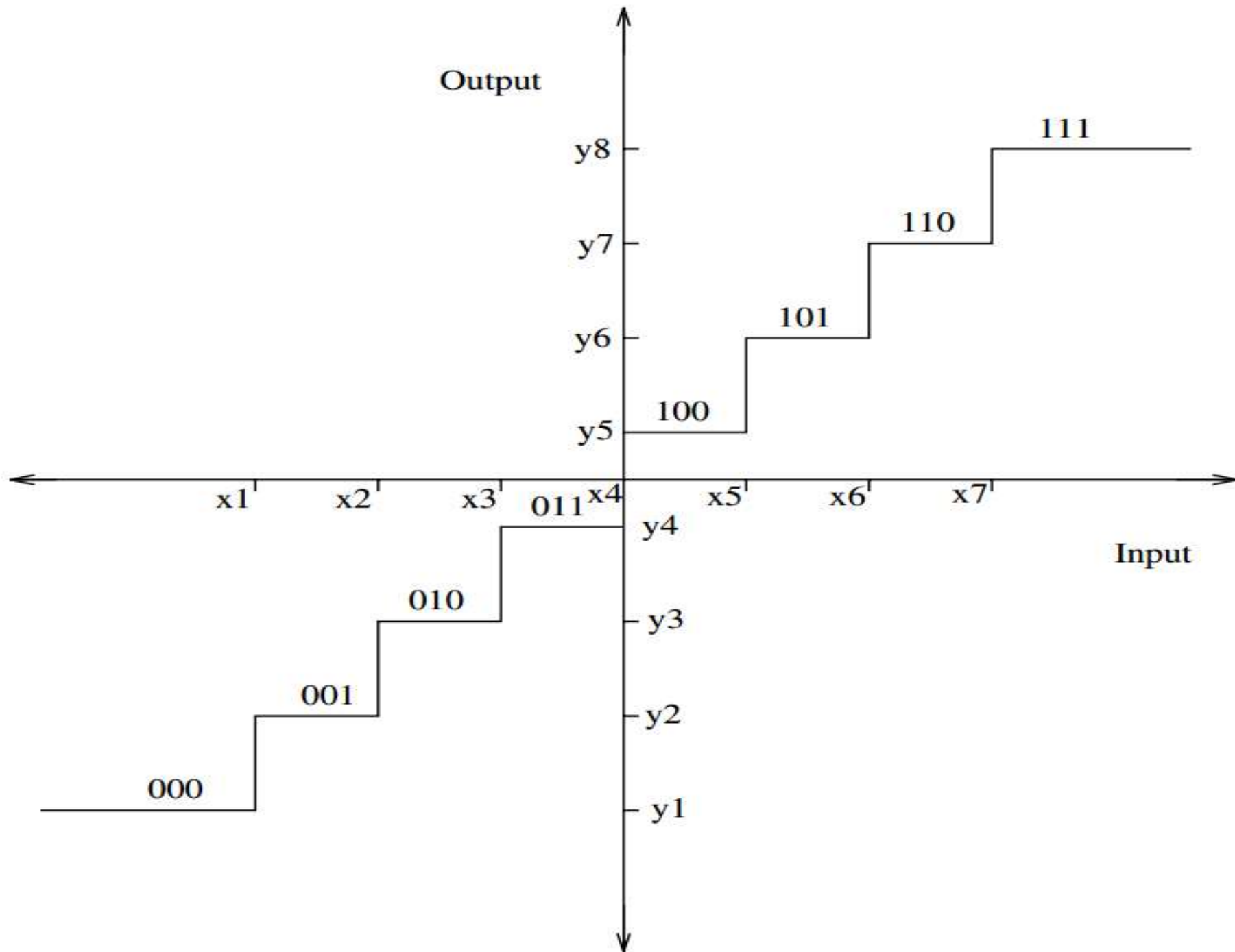
$$s_a(t) = \sum_{n=-\infty}^{\infty} s_a(nT) \frac{\sin[\pi(t - nT)/T]}{\pi(t - nT)/T}$$



# Scalar Quantization

- Quantization converts a continuous amplitude signal to a discrete-amplitude signal that is different from the continuous amplitude signal by the quantization error
  - When each of a set of discrete values is quantized separately the process is known as scalar quantization
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Output



## SQ Contd...

- Assuming all of the discrete amplitude values in the quantizer are represented by the same number of bits  $B$  and the sampling frequency is  $f_s$ , the channel transmission bit rate is given by

$$T_c = Bf_s \text{ bits/second}$$

- Given fixed  $f_s$ , the only way to reduce bit rate is by reducing number of bits  $B$
- In order to reduce the bit rate while maintaining good speech quality, various types of scalar quantizer have been designed

# Quantization Error

- The signal lying in the  $i^{\text{th}}$  interval,

$$x_i - \frac{\Delta_i}{2} \leq s(n) < x_i + \frac{\Delta_i}{2}$$

is represented by the quantized amplitude  $x_i$

- The mean squared error of the signal is given by

$$E_i^2 = \int_{x_i - \frac{\Delta_i}{2}}^{x_i + \frac{\Delta_i}{2}} (x - x_i)^2 p(x) dx$$

# Quantization Error Contd..

- Assuming that  $\Delta_i$  is small, we can assume that  $p(x)$  is flat within the interval  $x_i - \Delta/2$  to  $x_i + \Delta/2$
- Representing the flat region of  $p(x)$  by its value at the center,  $p(x_i)$ , the previous equation can be written as

$$E_i^2 = p(x_i) \int_{-\frac{\Delta_i}{2}}^{\frac{\Delta_i}{2}} y^2 dy = \frac{\Delta_i^3}{12} p(x_i)$$

# Quantization Error Contd..

- The probability of the signal falling in the  $i^{\text{th}}$  interval is

$$\Gamma_i = \int_{x_i - \frac{\Delta_i}{2}}^{x_i + \frac{\Delta_i}{2}} p(x) dx = p(x_i) \Delta_i$$

- Substituting this equation in the previous equation we have

$$E_i^2 = \frac{\Delta_i^2}{12} \Gamma_i$$

- And the total means squared error

$$E^2 = \frac{1}{12} \sum_{i=1}^N \Gamma_i \Delta_i^2$$



# Uniform Quantizer

- In a uniform quantizer, all of the quantizer intervals (steps) are the same width
- A uniform quantizer can be defined by two parameters: the number of quantizer levels and the quantizer step size  $\Delta$
- The step size is given by

$$\Delta = \frac{2X_{max}}{2^B}$$

- The quantization error is bounded by

$$-\frac{\Delta}{2} \leq e_q(n) \leq \frac{\Delta}{2}$$

# Uniform Quantizer Contd...

- The only way to reduce the quantization error is by increasing the number of bits
- When a uniform quantizer is used, it is assumed that the input signal has a uniform probability density function varying between  $\pm X_{\max}$ , with magnitude  $1/2X_{\max}$

# Uniform Quantizer Contd...

- The power of the input signal can be written as

$$P_x = \int_{-X_{max}}^{X_{max}} x^2 p(x) dx = \frac{X_{max}^2}{3}$$

- The signal to Quantization error ratio is given by


$$SNR = \frac{P_x}{P_n} = \frac{X_{max}^2/3}{\Delta^2/12}$$

$$SNR = \frac{P_x}{P_n} = 2^{2B}$$

$$SNR(dB) = 10 \log_{10}(2^{2B}) = 20B \log_{10}(2) = 6.02B \text{ dB}$$



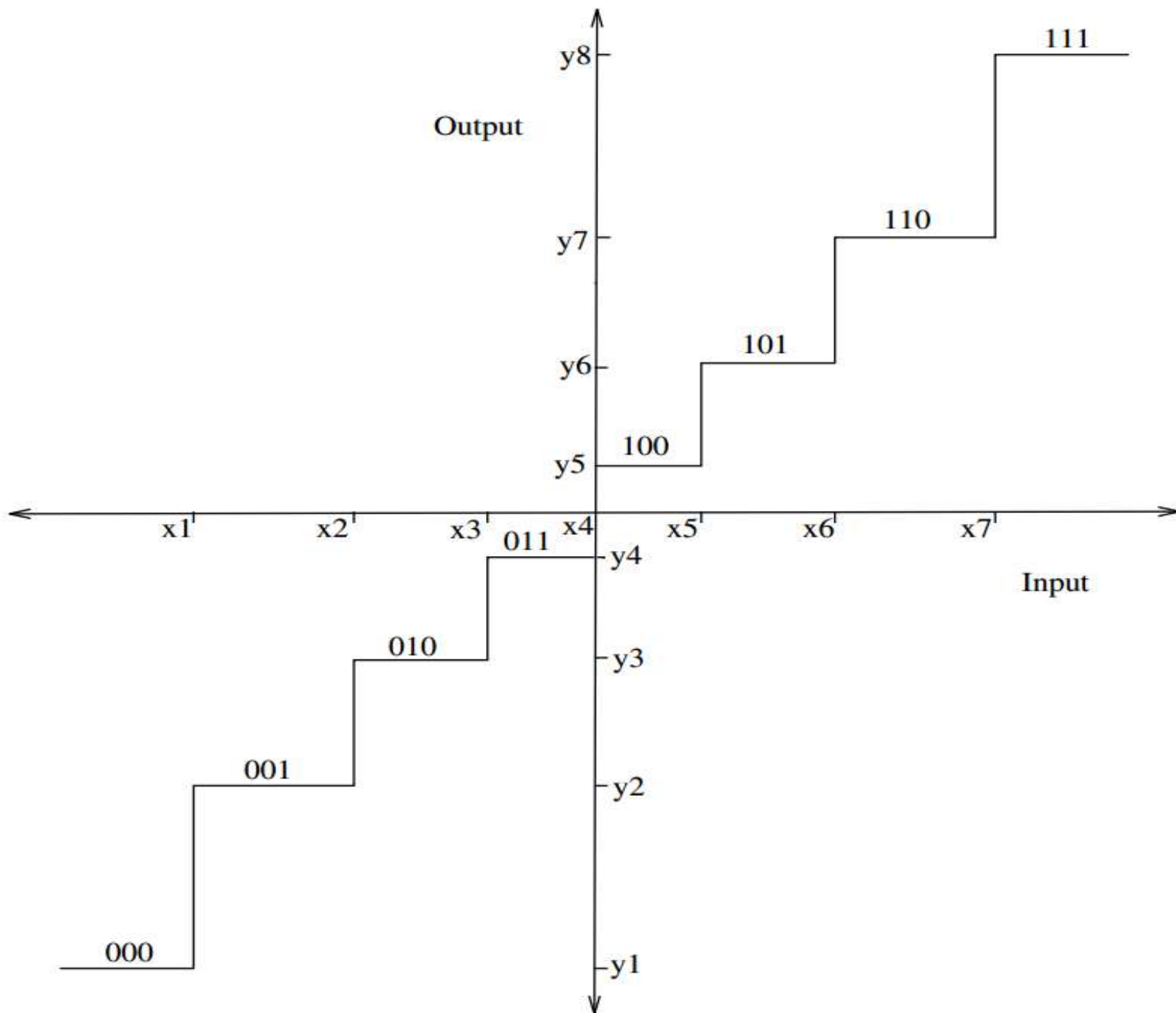
# Optimum Quantizer

- In order to maximize SNR for a given number of bits per sample, levels of the quantizer must be selected to match the probability density function of the signal to be quantized
  - This is because speech-like signals do not have a uniform probability density function, and the probability of smaller amplitudes occurring is much higher than that of large amplitudes
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# Optimum Quantizer Contd...

- Consequently, the optimum quantizer should have quantization levels with nonuniform spacing
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# Optimum Quantizer Contd...


- Consequently, the optimum quantizer should have quantization levels with nonuniform spacing
  - The noise contribution of each interval depends on the probability of the signal falling into a certain quantization interval
  - The nonuniform spacing of the quantization levels is equivalent to a nonlinear compressor  $C(x)$  followed by a uniform quantizer
  - The less likely higher sample values are compressed more than the more likely low amplitude samples
- 








# Optimum Quantizer Contd...

- Nonuniform quantization is advantageous in speech coding because
    - ▣ It matches the speech probability density function better and hence produces higher signal to noise ratio
    - ▣ Lower amplitudes, which contribute more to the intelligibility of speech, are quantized more accurately in a nonuniform quantizer
  - In speech coding, Max's quantizer is widely used to normalize the input samples to unit variance
- 




# Logarithmic Quantizer

- An optimum quantizer is advantageous if the dynamic range (or variance) of the input signal is fixed to a small known range
  - The performance of such a quantizer deteriorates rapidly as the power of the signal moves away from the value that the quantizer is designed for
- 



# Logarithmic Quantizer Contd...

- Logarithmic quantizers performances do not change significantly with changing signal variance and remain relatively constant over a wide range of input speech levels
  - In a companding quantizer, quantizer levels are closely spaced for small amplitudes which progressively increase as the input signal range increases.
- 

# Logarithmic Quantizer Contd...

- The A-Law compression is defined by


$$A_{Law}(x) = \frac{Ax}{1 + \log_{10}(A)} \quad \text{for } 0 \leq x \leq \frac{1}{A}$$
$$A_{Law}(x) = \frac{1 + \log_{10}(Ax)}{1 + \log_{10}(A)} \quad \text{for } \frac{1}{A} \leq x \leq 1$$

- The u-law compression is given by

$$\mu_{Law}(x) = \text{sign}(x) \frac{V_o \log_{10} \left[ 1 + \frac{\mu|x|}{V_o} \right]}{\log_{10}[1 + \mu]}$$




# Logarithmic Quantizer Contd...

- A comparison showed that the optimum quantizer can be as much as 4dB better, however
    - An optimum quantizer may have more background noise when the channel is idle
    - Its dynamic range is limited to a smaller input signal range
  - For these two reasons, logarithmic quantizers are usually preferred
- 




# Adaptive Quantizer

- Although, the probability density function of speech can easily be estimated and used in a quantizer design process, the variations in its dynamic range, which can be as much as 30dB, reduces the performance of any quantizer
  - One solution is estimating the variance of the speech segment prior to quantization and hence, adjusting the quantizer levels accordingly
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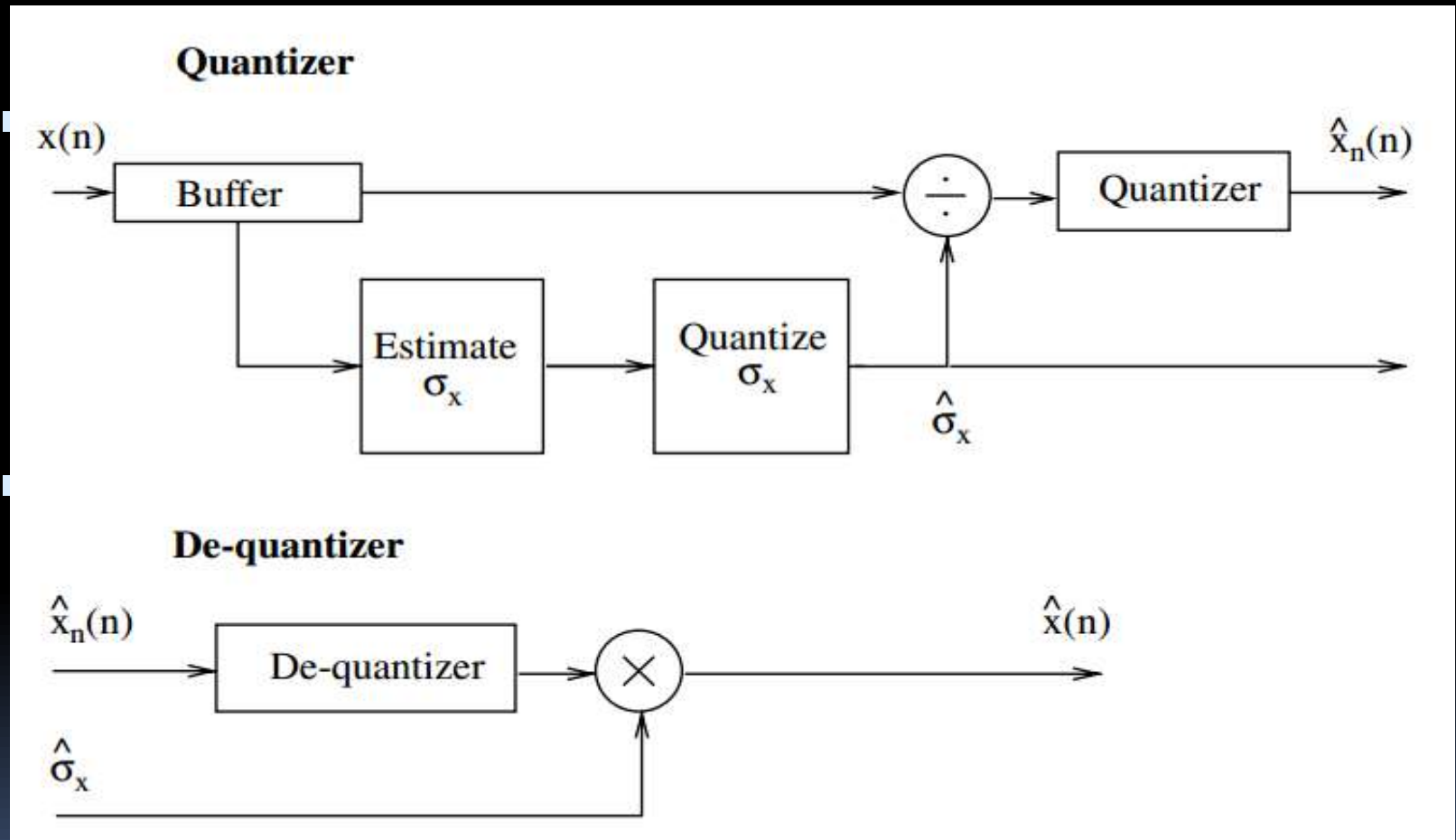


# Adaptive Quantizer Contd..

- The adjustment of the quantizer levels is equivalent to designing the quantizer for unit variance and normalizing the input signal before quantization
  - This is called forward adaptation
- 



# Adaptive Quantizer Contd..



# Adaptive Quantizer Contd..

- Assuming the speech is stationary during K samples, the rms is given by

$$\sigma_x = \sqrt{\frac{1}{K} \sum_{n=1}^K x(n)^2}$$

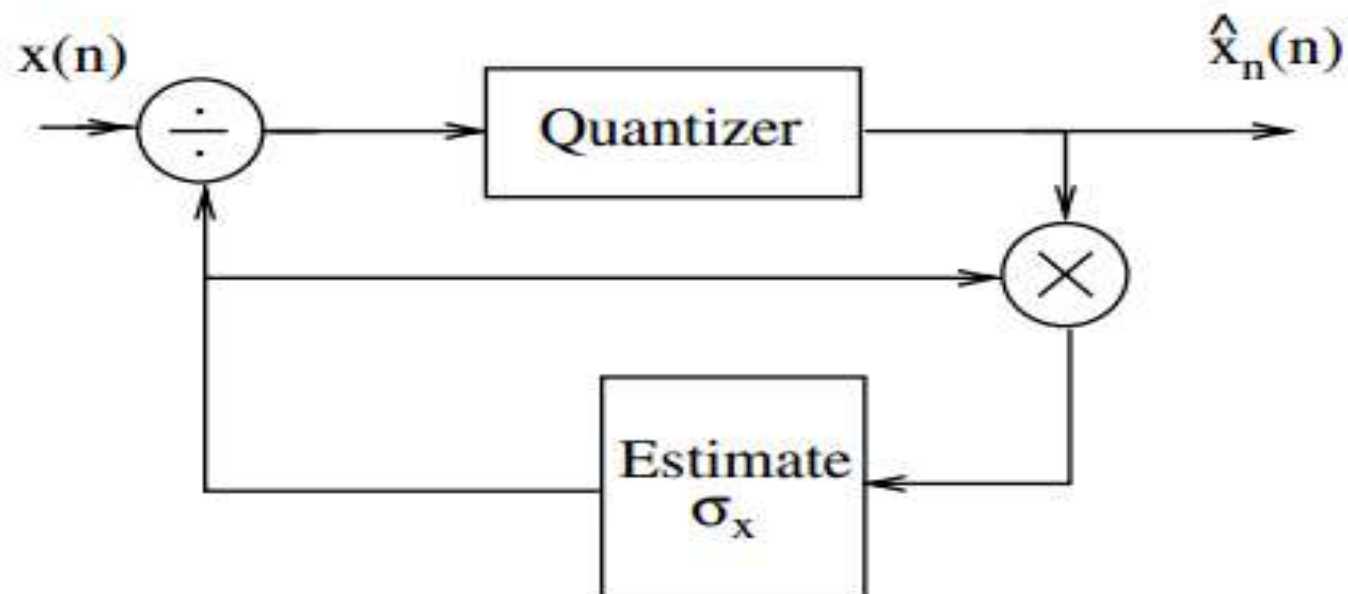
- The choice of block length K is very important because the probability density function of the normalized input signal can be affected by K

# Adaptive Quantizer Contd..

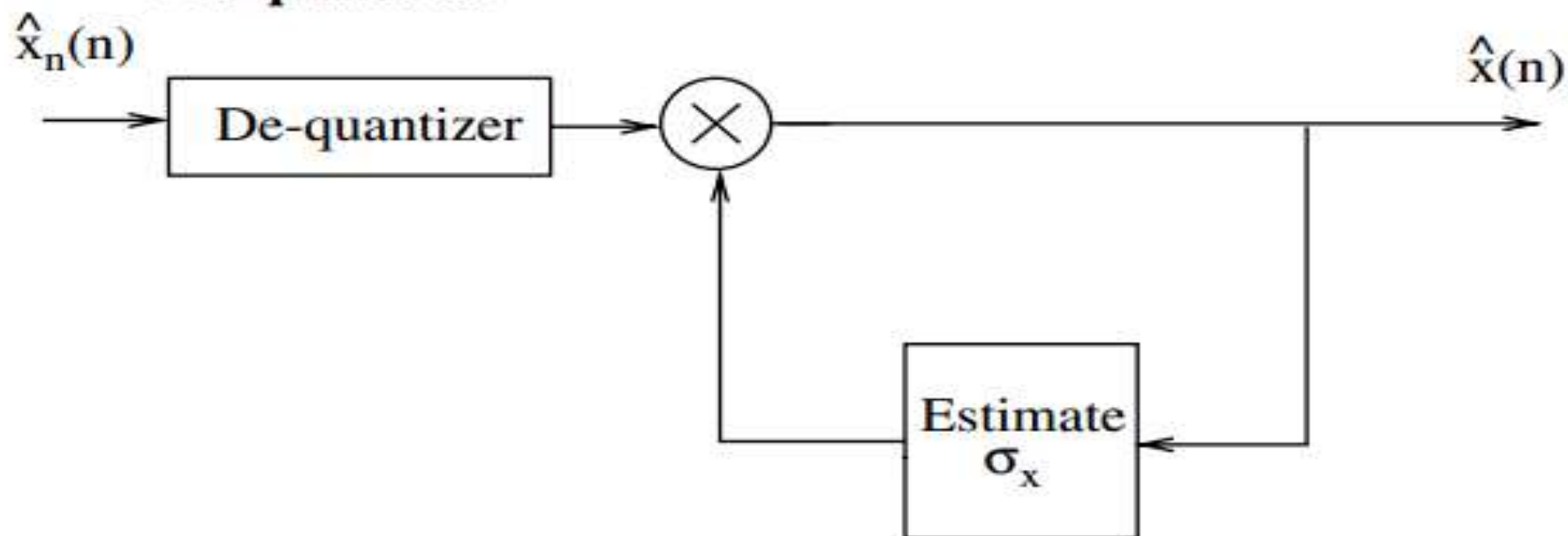
- Another adaptation scheme which does not require transmission of the speech variance to the de-quantizer is called backward adaptation
- Before quantizing each sample, the rms of the input signal is estimated from N previously quantized samples
- The normalizing factor for the  $n^{\text{th}}$  sample is

$$\sigma_x(n) = \sqrt{\frac{a_1}{N} \sum_{i=1}^N \hat{x}^2(n-i)}$$

## Quantizer



## De-quantizer



# Adaptive Quantizer Contd..

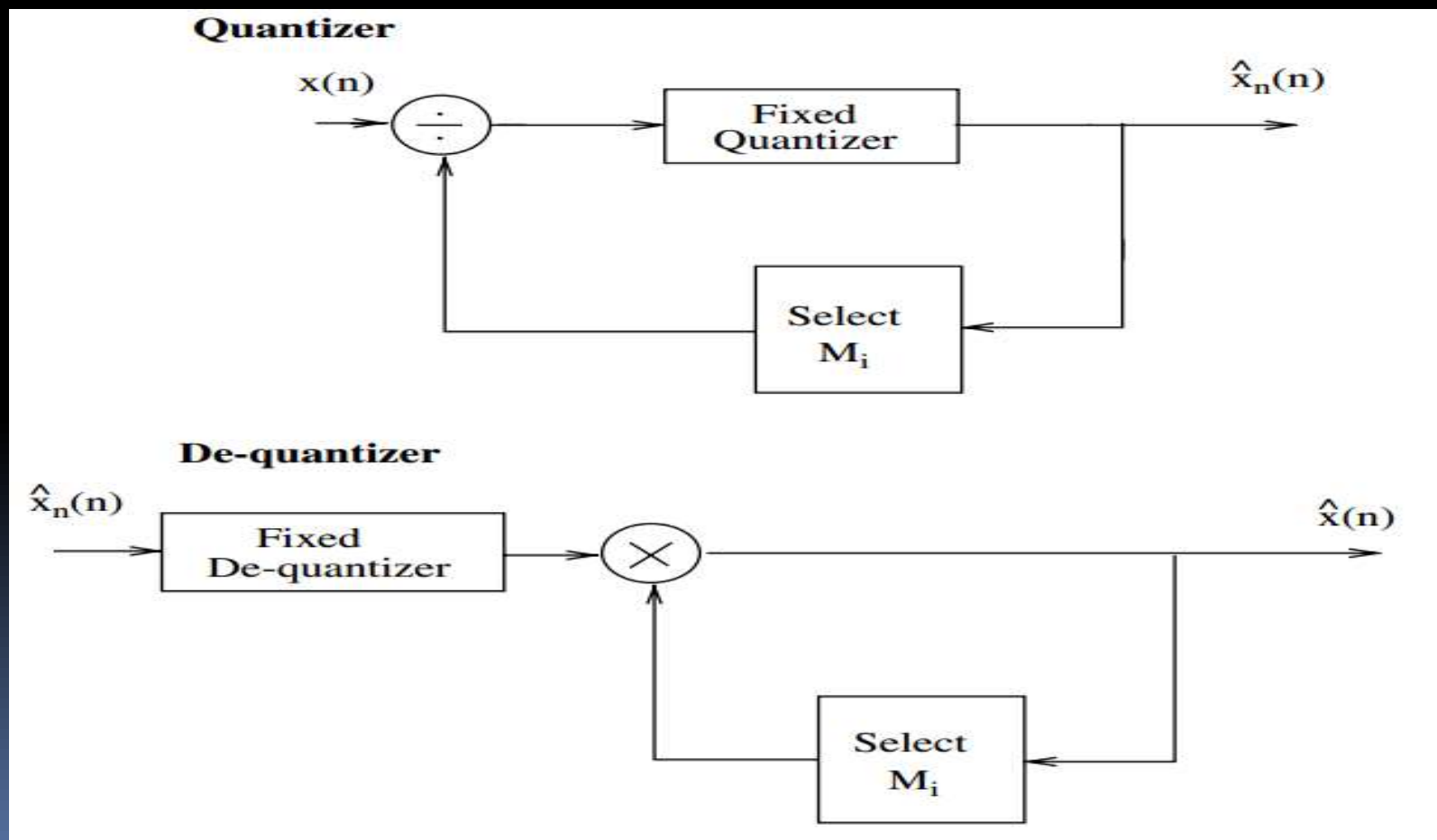
- One word memory

$$\Delta_{n+1} = \Delta_n M_i(|\hat{x}(n)|)$$

- where,  $M_i$  is one of  $i$  fixed coefficients corresponding to quantizer levels which control the expansion compression processes
- For large quantized previous samples, multiplier values are greater than one and for small previously quantized samples multiplier values are less than one

# Adaptive Quantizer Contd..

- One word memory



# Differential Quantizer

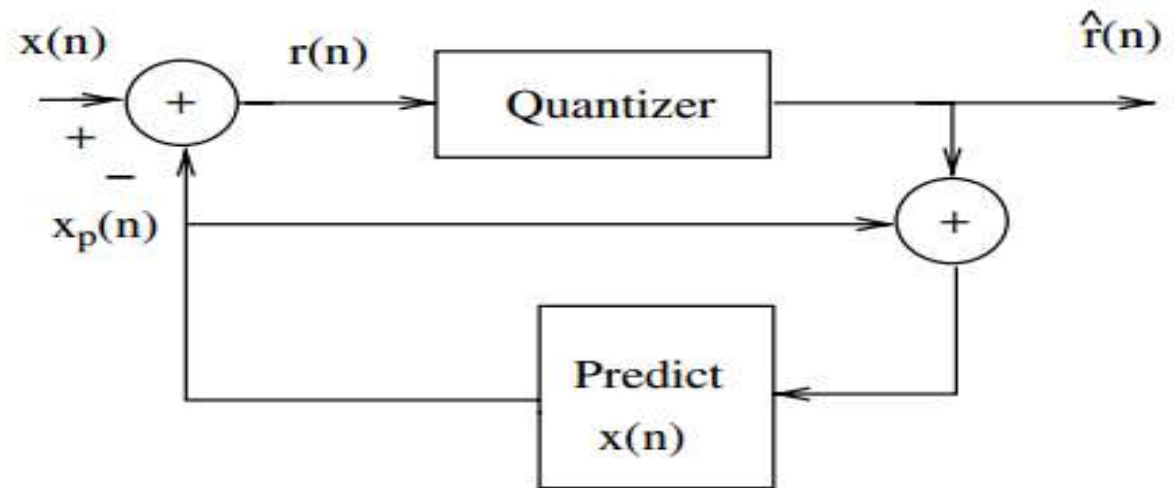
- In a differential quantizer, the final quantized signal,  $r(n)$  is the difference between the input samples  $x(n)$  and their estimates  $x_p(n)$

$$r(n) = x(n) - x_p(n)$$

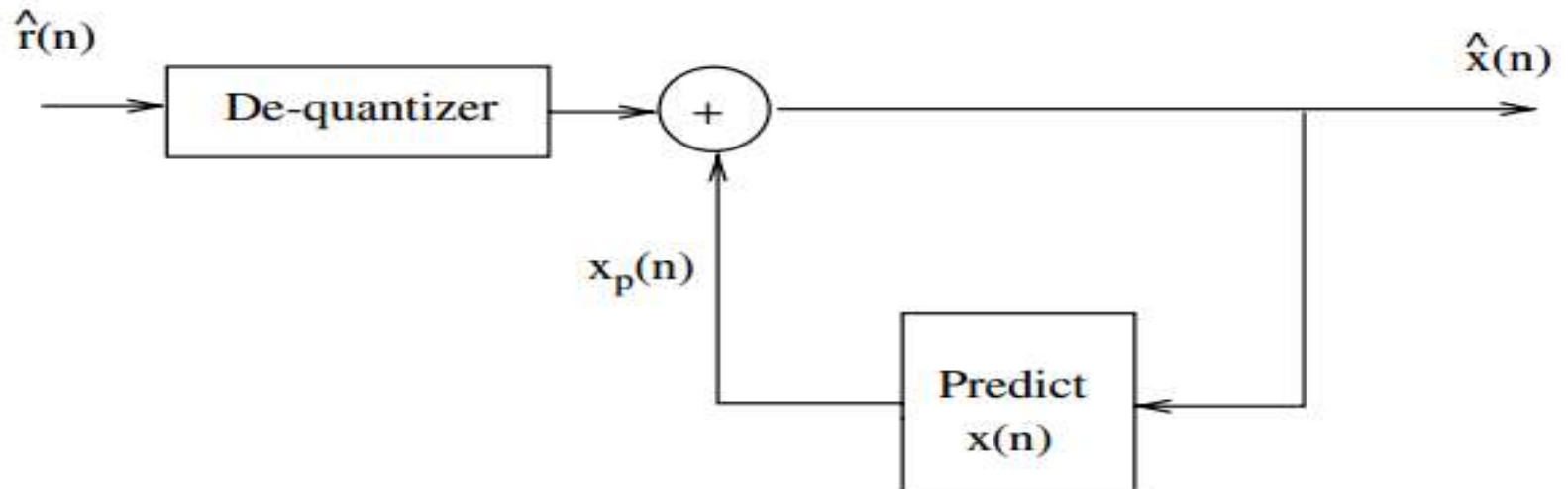
$$x_p(n) = \sum_{k=1}^p \hat{x}(n-k)a_k$$

# Differential Quantizer

**Quantizer**



**De-quantizer**











Thank You