# ECE462 – Lecture 11

• Autocorrelation Function

# Given a sequence of samples x[n], n = 0, 1, ..., N - 1

The sample autocorrelation function is defined as follows

$$R_{x}(k) = \frac{1}{N} \sum_{n=0}^{N-k-1} x[n]x[n+k] \text{ where } 0 \le p \le N, k = 0, 1, 2 \dots, P$$

- Assume that x[n] is a stationary sequence with zero mean
- The  $R_{\chi}(k)$  is an expression of the correlation among samples of x[n]
- If  $R_x(k) = 0, k \neq 0$  and x[n] is zero mean then the samples x[n] are uncorrelated
- $R_x(0) = Power of x[n]$
- If R<sub>x</sub>(k) ≠ 0, k ≠ 0 then there is correlation between samples of x[n] and thus, any sample of x[n] can be partially predicted from other samples of x[n].
- $R_x(0) \ge R_x(k), k \ne 0$
- If R<sub>x</sub>(k), k ≠ 0 is relatively significant then, sudden changes in neighboring samples of x[n] are highly non-probable.
- For real signals  $R_{\chi}(-k) = R_{\chi}(k)$

Consider "predicting" or estimating the sample x[n] at time n based on a linear combination of p past samples.

$$\hat{x}[n] = \sum_{i=1}^{r} a_i x[n-i]$$

Where  $\{a_i\}$ , i=1,...,p are the "prediction" coefficients to be determined. One way to calculate  $\{a_i\}$  is to minimize the Mean Square Error between the "true" and "predicted value", i.e.,

*Minimize*<sub>*w.r.t.*{*a<sub>i</sub>*} 
$$\sum_{n=1}^{N} (x[n] - \hat{x}[n])^2$$</sub>

#### **Solution:**

$$\sum_{i=1}^{P} a_i R_x(j-i) = R_x(j), j = 1, 2, ..., p$$

- In practice p is chosen arbitrarily.
- Notice that if  $R_{\chi}(k) = 0$ ,  $k \neq 0$  then prediction is not possible
- To find {a<sub>i</sub>}, repeat the last equation for j=1,...,p, to form a linear system of equations

$$\begin{array}{c} P_{x}(o) \ P_{x}(i) \ P_{x}(2) \cdots P_{x}(P-1) \\ P_{x}(i) \ P_{x}(o) \ P_{x}(1) \cdots P_{x}(P-2) \\ \vdots \\ P_{x}(P-1) \cdots P_{x}(o) \ P_{x}(1) \cdots P_{x}(o) \\ P_{x}(e^{-1}) \cdots P_{x}(e^{-1}) \\ P_{x}(e^{-1}) \cdots P_{x}(e^{-1}) \\ P_{x}(e^{-1}) \end{array}$$

• Ex: Let 
$$R_x(k) = 0.5^k$$
,  $k = 0,1...$   $R_x(-K) = R_x(K)$   
Let us choose p = 2

$$\begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} 0.5 \\ 0.25 \end{bmatrix} \Rightarrow \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} 1 & -0.5 \\ -0.5 & 1 \end{bmatrix} \begin{bmatrix} 0.25 \\ 0.25 \end{bmatrix}$$
$$\Rightarrow a_1 = 0.566, a_2 = 0$$

Given a sequence x[n], n=0,1,...



- The dynamic range of e[n] is much smaller than the dynamic range of x[n]. Therefore, coding can be more efficient (lower bit-rate).
- If Quantization is need prior to coding then the operation becomes lossy.

• Predictive decoder





 However, this arrangement does not guarantee that encoder and decoder see the same quantization error. Actually, quantization errors propagate at decoder.



- Using feedback prediction at the encoder side prevents propagation of the quantization error at the decoder side (Both sides see the same quantization error)
- Example:

Suppose we use DPCM where:

Prediction:  $\hat{x}[n] = x[n-1], n = 0, 1, 2 \dots$ Quantization: Q[x] = truncation[x]Input signal:  $N = 0 \quad 1 \quad 2 \quad 3 \quad 4 \quad 5 \quad 6 \quad 7$ x[n] = 20, 38-2, 56+, 74-6, 92-7, 10-7, 12-7, (47-2)

- Calculate the sequence  $\tilde{e}[n]$  as well the reconstructed  $\tilde{x}[n]$  for the two cases of using Encoder A (forward prediction) and Encoder B (feedback prediction).
- Observe and comment on the effect of quantization noise in the two cases.

<u>Answer</u>

• So the error increases due to the propagation of quantization errors.

• Encoder B

• Decoder B

• So clearly in the second case where feedback prediction is employed during encoding and decoding the effect of quantization errors is less.