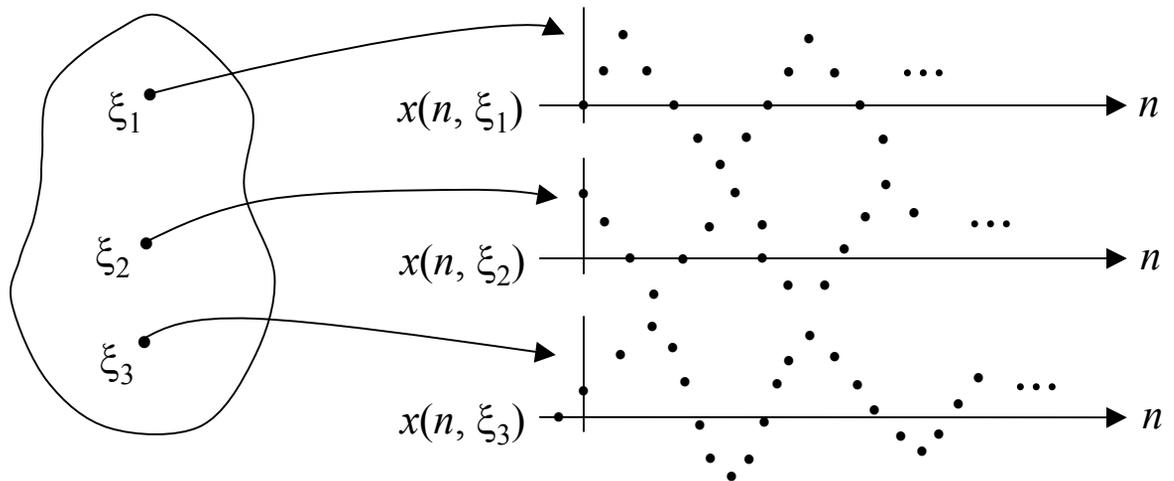


II. Random Processes

- Random signal/sequence definition
- Signal mean, variance, autocorrelation & autocovariance sequence, normalized cross-correlation sequence
- Statistical characterization of random signals
 - Stationarity
 - Wide sense stationarity (wss)
 - Jointly wide sense stationarity (jointly wss)
 - Signal average
 - Ergodicity
 - I.I.D. Random process
 - Concept of white noise, Bernoulli process, Random walk
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- Periodic random process
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- Frequency domain description for a stationary process
 - Power spectral density (PSD) definition & properties
- Complex spectral density function: definition & properties
- Innovation Representation of random vectors
 - DKLT
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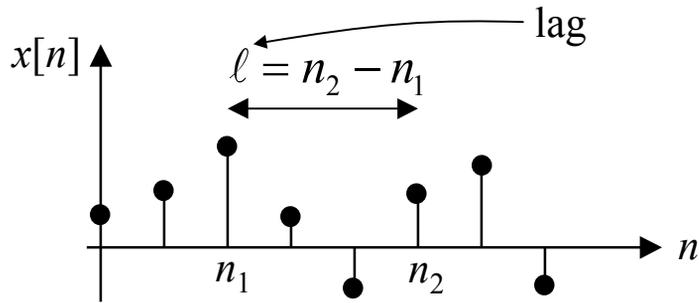
II. Random Processes

❖ Random Signal/Sequence:



- Consider sequence $x[n] = x(n, \xi)$ ← for a fixed n $x[n]$ is a RV
- $x[n]$: discrete random signal/ random sequence
- $x(n, \xi)$ for fixed ξ : realization of the random process (trial)

Example: $x(n, \xi) = \xi \cos(\pi n / 10)$, where $\xi = U[0, 1]$.



❖ Signal mean value (ensemble average):

$$m_x(n) =$$

❖ Signal variance:

$$\sigma_x^2(n) =$$

❖ Signal autocorrelation sequence:

$$R_{xx}(n_1, n_2) =$$

❖ Signal autocovariance sequence:

$$C_{xx}(n_1, n_2) =$$

❖ Signal cross-correlation sequence:

$$R_{xy}(n_1, n_2) =$$

❖ Signal cross-covariance sequence:

$$C_{xy}(n_1, n_2) =$$

❖ Normalized cross-correlation sequence:

$$\rho_{xx}(n_1, n_2) =$$

❖ Statistical Characterization of Random Signals:

- Random signals are characterized by joint distribution (or density) of samples
- $F_x(x_1, x_2, \dots, x_k, n_1, \dots, n_k)$
 $= \Pr [x(n_1) \leq x_1, \dots, x(n_k) \leq x_k]$
- $F(\cdot)$ is highly complex to compute - difficult to obtain in practice

❖ Stationarity:

Definition: a RP is said to be stationary if any joint density or distribution function depends only on the spacing between samples, not where in the sequence the samples occur

Example: $f_x(x_1, x_2, \dots, x_N; n_1, \dots, n_N)$
 $= f_x(x_1, x_2, \dots, x_N; n_{1+k}, \dots, n_{N+k})$

for any value of k

If $x(n)$ is stationary for all orders $N = 1, 2, \dots$

$x(n)$ is said to be strict-sense stationary.

Example: Stationary up to order 2 \rightarrow wide-sense stationary.

❖ Wide-Sense Stationarity:

➤ *Definition*: a RS $x(n)$ is called wide-sense stationary (WSS) if

(1) the mean is a constant independent of “ n ”

(2) the autocorrelation depends only on the distance $\ell = n_1 - n_2$ (i.e., $x(n)$ is a seq. of uncorrelated RVs)

Consequence: the variance is a constant independent of “ n ”

❖ Wide-Sense Stationarity (con't):

➤ *Definition:* $x[n]$ and $y[n]$ are said to be w.s. jointly stationary if:

1) $x[n]$ and $y[n]$ are wss stationary

$$2) R_{xy} [n_1, n_0] = R_{xy} [n_1 - n_0]$$

➤ When $x[n]$ and $y[n]$ are w.s.j stationary:

$$R_{xy} [n_1, n_0] = R_{xy} [n_1 - n_0] =$$

$$C_{xy} [n_1, n_0] = C_{xy} [n_1 - n_0] =$$

➤ Properties:

$$R_{xy}(k) =$$

$$C_{xy}(k) =$$

❖ Example

Let $x(n)$ be a real valued process of independent variables each with mean m and variance σ_x^2 .

1) Compute: $R_x(k,n)$ & $C_x(k,n)$

2) Let $y(n)$ be defined as:

$$y(n) = x(n) + x(n-1)$$

Compute: $R_y(k,n)$ & $C_y(k,n)$

❖ Signal (time) Average:

$$\langle x[n] \rangle =$$

❖ Ergodicity:

- in many applications only one realization of a RP is available
- in general, one single member doesn't provide information about the statistics of the process
- except when process is stationary + ergodic: statistical information can be derived from one realization of RP
- **Def:** a RP is called ergodic if:
 - all ensemble averages = all corresponding time averages
- Ergodicity in the mean:
 - Def:** a RP is said to be ergodic in the mean if:
- Ergodicity in correlation:
 - Def:** a RP is said to be ergodic in correlation if:

❖ Example: Independent, Identically Distributed (I.I.D.) Random Process (RP):

A Random Process is said to be:

. an *independent process* if:

$$f_x(x_1, x_2, \dots, x_k; n_1, \dots, n_k) = f_1(x_1; n_1) \dots f_k(x_k; n_k)$$

. if all RVs have the same pdf $f(x) \Rightarrow x(n)$ is called I.I.D.

Note: I.I.D. processes have no memory, where a future value would depend on past values

• Mean of I.I.D. Process:

$$m_x(n) =$$

Autocovariance:

$$C_x(n_1, n_2) =$$

Autocorrelation:

$$R_x(n_1, n_2) =$$

❖ RP Example: White noise

Definition: A random sequence $w(n)$ is called a white noise process with mean m_w and variance σ_w^2 iff

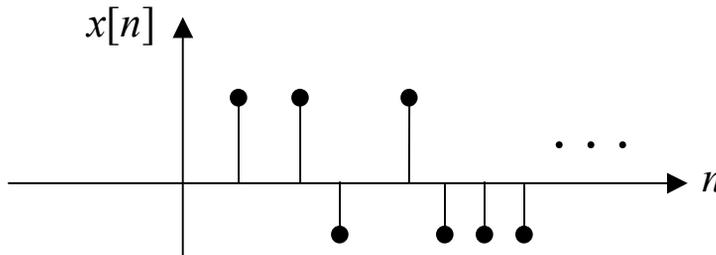
$$E\{w(n)\} = m_w$$
$$R_w(k) = \sigma_w^2(k)$$

Notes:

- 1) all frequencies contribute the same amount (as in the case of white light, therefore the name of “white noise”)
- 2) if the pdf of $w(n)$ is Gaussian: it is called “white Gaussian noise”

❖ RP Example: Bernoulli Process

a binary sequence – independent samples



$$\begin{aligned}x[n] &= 1 && \text{with probability } P \\ &= -1 && \text{with probability } (1 - P)\end{aligned}$$

➤ for $P = 1/2$ process is called binary white noise

- Probabilistic description:

➤ $Pr [x(0) = 1, x(1) = 1, x(2) = -1] =$

➤ is the process stationary?

Mean	Variance

❖ Application of Bernoulli process:

$P[\text{first 4 independent bits in a binary sequence are } 1001] =$

❖ RP Example: Random Walk

- Consider a sequence of I.I.D. RVs $\{X_i\}$
- Define $S_n = X_1 + X_2 + \dots + X_n \quad n = 1, 2, \dots$
 $S_n = S_{n-1} + X_n \quad \leftarrow$ sum process
 $M_n = (1/n) S_n \quad \leftarrow$ arithmetic mean process
- The process S_n is called random walk when
 $X_i = \pm 1$ (Bernoulli RVs)
- When $P = 1/2$ (for Bernoulli process) discrete Wiener process

Properties:

S_n has independent increments in non-overlapping
time intervals

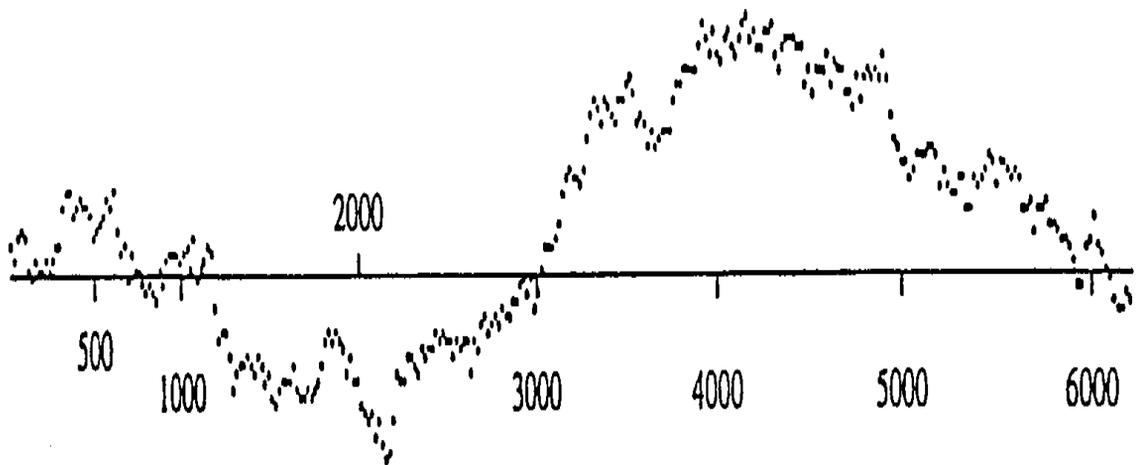
$$S_{n_1} - S_{n_2} =$$

$$S_{n_3} - S_{n_2} =$$

Random Walk: General Character

- Tends to have long runs of positive and negative values.
- Length of runs increases with increasing time, but local behavior remains the same.

Example of Random Walk:



❖ Random Process Properties

- A RP is said to be *orthogonal* if $x[n]$ is a sequence of orthogonal RVs, which means:

$$R_x(n_1, n_2) =$$

- A RP is said to be *wide-sense (ws) cyclostationary* if $\exists N$ such that

$$m_x(n) =$$
$$R_x(n_1, n_2) =$$

Example of a w.s. cyclostationary process:

Example: let $x(n)$ be a zero-mean, uncorrelated Gaussian sequence with variance $\sigma_x^2(n) = 1$

what can we say about $x(n)$?

(independent?, stationary?)

Example: let $x(n)$ be a RP generated as:

$$\begin{aligned}x(n) &= \alpha x(n-1) + w(n) & n \geq 0 \\x(-1) &= 0\end{aligned}$$

with $w(n)$ a stationary RP with mean m_w and correlation sequence $R_w(\ell) = \sigma_w^2 \delta(\ell)$

- a. find the mean $m_x(n)$
- b. is $x(n)$ stationary?

Example: let $x(n)$ be a binary white noise process

- a. compute the mean $m_x(n)$
- b. compute the correlation and covariance functions
- c. is $x(n)$ stationary?

Example: let $x(n)$ be a discrete Wiener process

- a. compute the mean and variance
- b. is the process stationary? wss?

Example: let $x(n)$ be a RP defined by a sequence of independent RVs with mean m and variance σ^2

- a. Compute the mean of the RP
- b. Compute the correlation of the RP
- c. let $y(n) = x(n) + \frac{1}{2}x(n-1)$
 - compute $R_y(n)$
 - is $y(n)$ stationary?

❖ Periodic Random Process

- if $x[n]$ is periodic, $x[n] =$
- Density function $f_x[n_0] x[n_1] \dots x[n_L] =$
- Mean

- Correlation

- Correlation for stationary periodic RP

Example: $x[n] = A \exp(j(\omega n + \theta))$, $\omega \sim U[0, 2\pi]$

Compute $R_x(k)$ and $m_x(k)$

❖ Correlation Function Properties

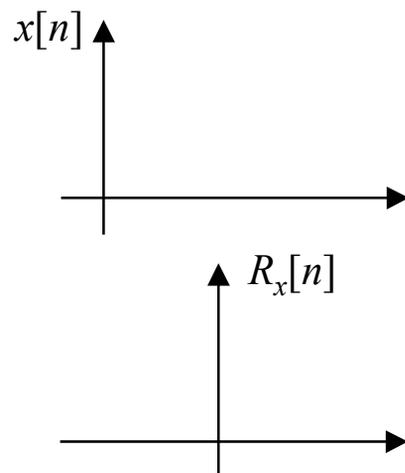
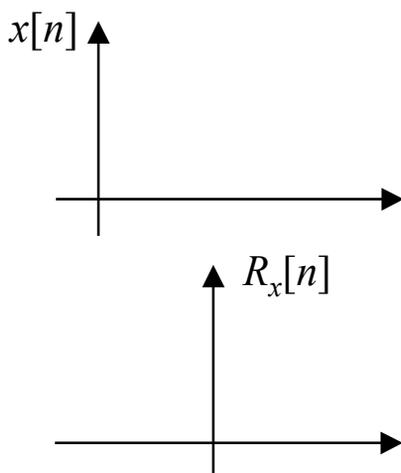
(1) Conjugate symmetry

(2) Positive semi-definite property

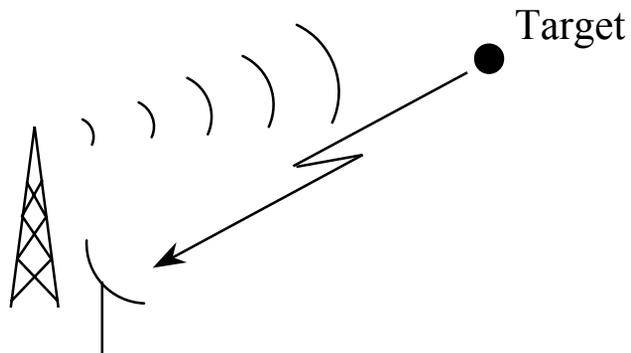
(3) $R_x(k)$ max at $k=0$

(4) High correlation

Low correlation



❖ Application to Radar Target Detection



assume $y(t) = x(t-T)$

❖ Application to Tone Detection in Noise

Property: if the process $x[n]$ is aperiodic then

$$\lim_{k \rightarrow \infty} R_{xx}[k] = 0$$

Example:

Assume we have a sinusoidal random signal $x[n]$ with variance 0.5 imbedded in wss white noise $w[n]$ with variance 16 (Signal and no. The correlation sequence may be used to get information on the properties of the periodic signal

- a) Compute the SNR
- b) Compute the expression for the correlation of the noisy signal $y[n]=x[n]+w[n]$.

❖ Correlation Matrix Properties for a Stationary Process

Assume $\underline{x} = [x(0), x(1)]^T$

➤ Recall: $R_x = E [\underline{x} \underline{x}^H]$

➤ Correlation Matrix for a Stationary Process

$x[n]$ stationary \Rightarrow

$R_x =$

➤ Correlation Matrix for a Periodic RP

➤ Correlation Matrix Properties

Assume $\underline{x}=[x(0), \dots, x(N-1)]^T$

(1) R_x is Hermitian

(2) R_x is positive semi definite, i.e., $\lambda(R_x)$

(3) R_x has an eigendecomposition of the form

$$R_x = U\Lambda U^H$$

where: U is a unitary eigenvector matrix

Λ is a diagonal eigenvector matrix

➤ How to compute correlation estimates

$$\text{Assume } \begin{cases} x(t) \text{ known } t = 0 \rightarrow t = T_0 \\ x(t) \text{ ergodic (why?)} \end{cases}$$

- For discrete data: $\underline{x} = [x(0), \dots, x(N)]^T$

$$\hat{R}_x(k\Delta t) =$$

- Quality of estimate? → find mean and variance of $\hat{R}_x(k\Delta t) =$

$$(1) E[\hat{R}_x(k)] =$$

$$(2) \text{ Var} \left[\hat{R}_x(k) \right] \cong \frac{N}{[N-k]^2} \sum_{i=-\infty}^{\infty} \left[R_x^2(i) + R_x(i+k)R_x(i-k) \right]$$

when $N \gg k$

Alternate Estimator: Biased Estimator

$$\tilde{R}_x(k\Delta t) =$$

Quality of estimate:

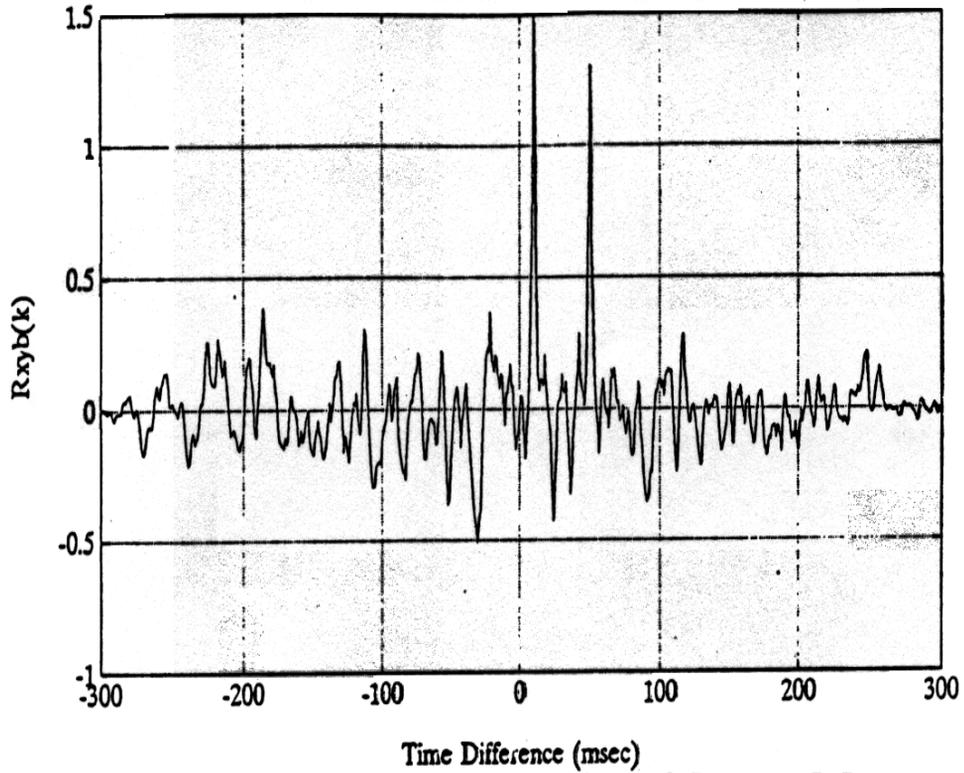
$$(1) \quad E[\tilde{R}_x(k\Delta T)] =$$

$$(2) \quad \text{Var}[\tilde{R}_x(k\Delta T)] \cong \frac{1}{N+1} \sum_{-\infty}^{\infty} [R_x^2(i) + R_x(i+k)R_x(i-k)] \\ k > 0$$

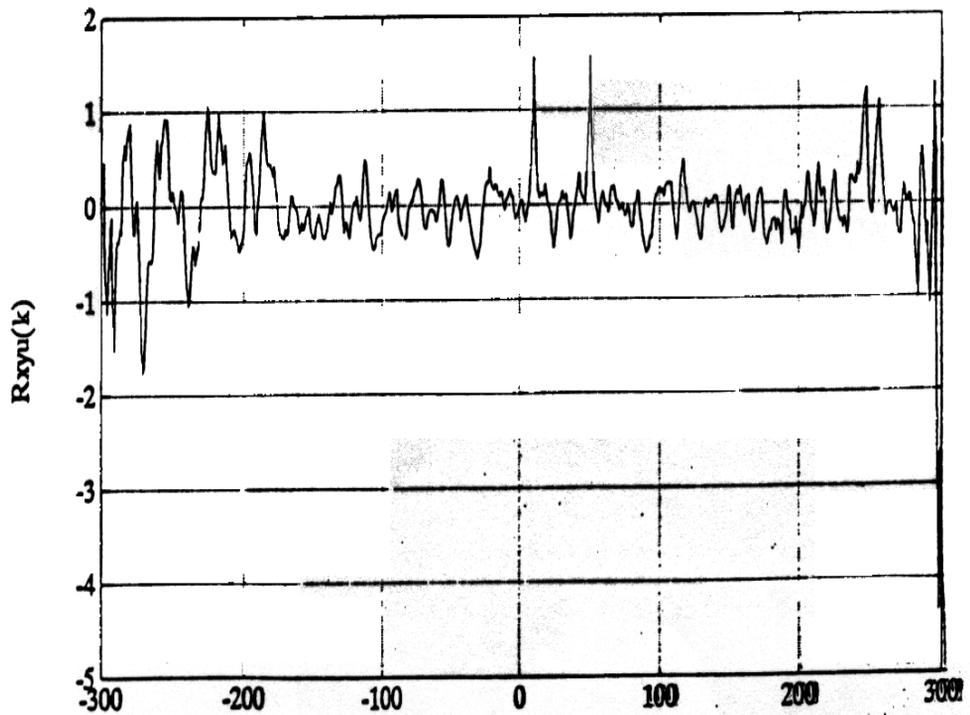
Biased/Unbiased estimator Summary

Biased Estimator	Unbiased Estimator
$\tilde{R}_x(k\Delta T) = \frac{1}{N+1} \sum_{i=0}^{N-k} x(i)x(i+k)$	$\hat{R}_x(k\Delta T) = \frac{1}{N+1-k} \sum_{i=0}^{N-k} x(i)x(i+k)$
$E[\tilde{R}_x(k\Delta T)] = \frac{N-k+1}{N+1} R_x(k)$	$E[\hat{R}_x(k\Delta T)] = R_x(k)$
$\text{Var}[\tilde{R}_x(k\Delta T)] = \frac{1}{N+1} \mathcal{L}(R_x)$	$\text{Var}[\hat{R}_x(k\Delta T)] = \frac{N}{[N-k]^2} \mathcal{L}(R_x)$
<u>when $k \rightarrow N$</u>	
$\text{Var}[\tilde{R}_x(k)] \rightarrow K < \infty$	$\text{Var}[\hat{R}_x(k\Delta T)] \nearrow + \infty$
$E[\tilde{R}_x(k)] = \frac{1}{N+1} R_x(k)$	$E[\hat{R}_x(k)] \rightarrow R_x(k)$
<u>when $N \rightarrow +\infty$</u>	
$\text{Var}[\tilde{R}_x(k)] \searrow$	
$\text{bias of } E[\tilde{R}_x(k)] \searrow$	

Biased Cross-Correlation of datx and daty



Unbiased Cross-Correlation of datx and daty



➤ How to compute correlation matrix estimates

❖ Frequency Domain Description of Stationary Processes

➤ Power spectral density (PSD)

$$S_x(e^{j\omega}) =$$

$$R_x(\ell) =$$

➤ Example: find the PSD of zero-mean w.s.s. $x[n]$ with

$$r_x(\ell) = a^{|\ell|}$$

➤ PSD Properties

Let $x[n]$ be a stationary and periodic RP, then

- 1) $R_x(k)$ is periodic with the same period
- 2) $S_x(e^{j\omega})$ is periodic with period 2π

Proof:

❖ PSD has three key properties:

- (1) $P_1 = \left\{ \begin{array}{l} \text{PSD } S_x(e^{j\omega}) \text{ is a real-valued periodic function} \\ \text{of period } 2\pi \text{ for any } x[n] \\ \text{if } x[n] \text{ is real then } S_x(e^{j\omega}) \text{ is also even} \end{array} \right.$
- (2) $P_2 =$ the PSD $S_x(e^{j\omega})$ is non-negative definite;
I.e., $S_x(e^{j\omega}) \geq 0 \rightarrow$ see page 159, text
- (3) $P_3 =$ the area under $S_x(e^{j\omega})$ is non-negative and equals the energy of $x[n]$

Example: White Noise

Example: Harmonic Process

- *Definition:* a harmonic process is defined as:

$$x[n] = \sum_{k=1}^M A_k \cos(\omega_k n + \phi_k); \omega_k \neq 0$$

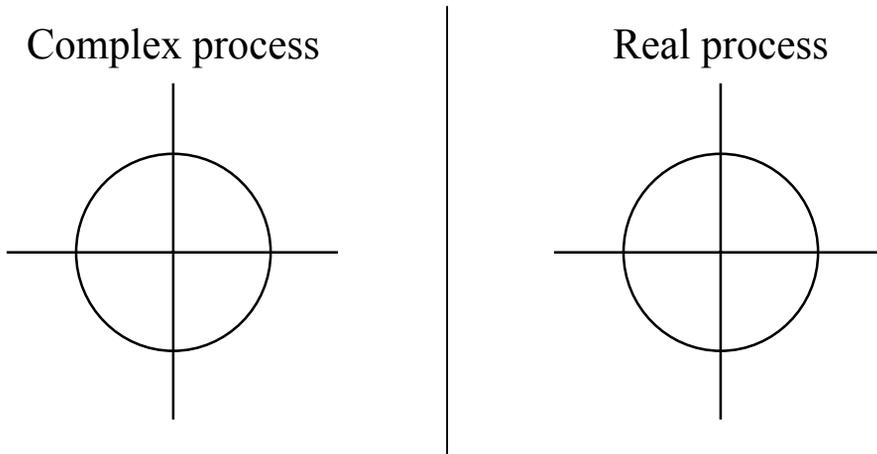
where M , $\{A_k\}$, $\{\omega_k\}$ are constants

$\{\phi_k\}$ are pairwise independent RVs
uniformly distributed over $[0, 2\pi]$

- Compute $E\{x[n]\}$ and $R_x(\ell)$, $S_x(e^{j\omega})$

Example: given $R_x(\ell) = \sigma^2 \rho^{|\ell|}$ $|\rho| < 1$
compute $S_x(e^{j\omega})$

❖ Properties for rational form (poles/zero location)



❖ Region of Convergence of $S_x(z)$

Example: $R_x(\ell) = \sigma^2 \rho^{|\ell|}$ $|\rho| < 1$

compute $S_x(z)$

❖ Summary of Properties for Stationary $x[n]$

Definitions	
Mean	
Correlation	
Covariance	
Cross-Correlation	
Cross-Covariance	
PSD	
Cross-PSD	

Inter-relations	
$C_x(\ell) =$	$C_{xy}(\ell) =$

Properties	
Autocorrelation	PSD

Properties	
Cross-correlation	Cross-PSD

➤ **Example:** $x[n] = Ae^{j\omega_0 n}$ A RV

compute $R_x(\ell)$

$S_x(e^{j\omega})$

❖ Innovation Representation of Random Vectors - the Discrete Karhunen-Loeve Transform (DKLT)

- In many practical applications, it is beneficial to represent a random sequence \underline{x} with a linearly equivalent sequence \underline{w} consisting of uncorrelated components (such sequence \underline{w} is called the *innovation representation*).
- In such cases, each component of the uncorrelated sequence \underline{w} can be viewed as adding new information to the previous components.
- Applications exist in compression, classification, etc...

➤ **How to transform \underline{x} into the innovation representation**

Assume $\underline{x}=[x(0),\dots,x(N-1)]^T$ is zero-mean

Questions:

(1) What does it mean for \underline{w} to be uncorrelated ?

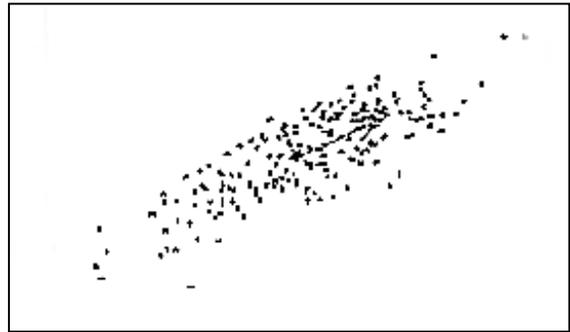
(2) What does “represent a random sequence \underline{x} with a linearly equivalent sequence \underline{w} ” mean ?

Assume $A=U^H$

►DKLT Applications

DKLT is used in data compression (speech/image coding) as it allows for a lower dimensional representation of the data.

Example: Assume we have 200 samples of two-dimensional data of type $\underline{x}=[x_1, x_2]$.



Estimated correlation matrix is given by:

$$\mathbf{R}_x =$$

Compression set-up

