

Definitions

① auto correlation $R_{xx}(n, n+m)$: Measures the similarity of R.P. $X(t)$ at time n and $X(t)$ at later time $n+m$.

$$R_{xx}(n, n+m) = E\{X(n) X^*(n+m)\}$$

② stationary process.

This is a random process whose statistics do not change with shift in time origin.

③ wide Sense Stationary process:

This is a random process $X(t)$ which satisfies the following conditions:

1. its mean is constant. i.e $E[X] = \text{constant}$.
2. auto correlation depends only on time interval 'm'.

i.e $R_{xx}(n, n+m) = R_{xx}(m)$.

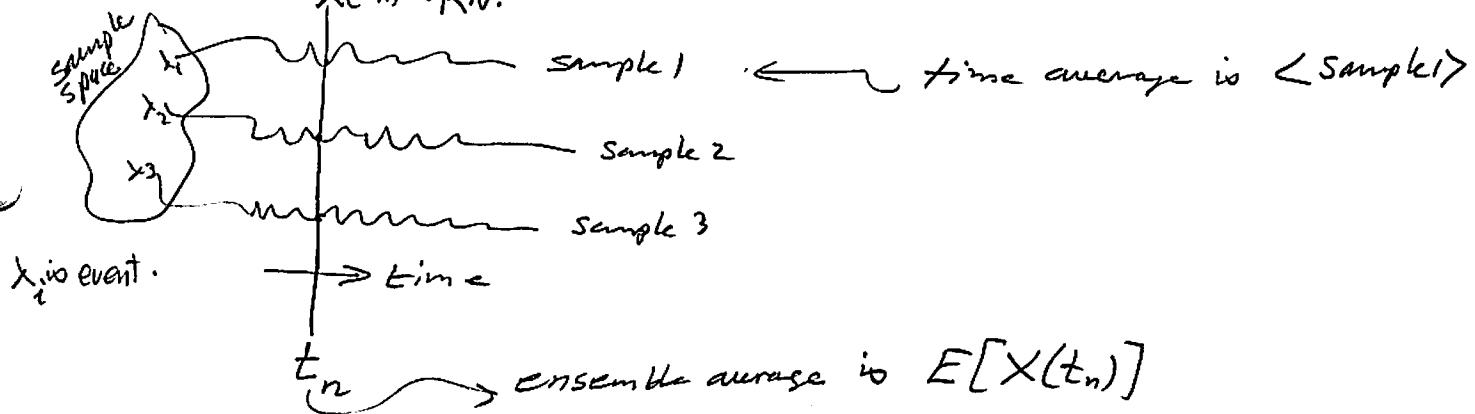
Notice that stationary process is WSS, but WSS is not necessarily stationary i.e WSS



④ Time averages, Ensemble averages

Time average is the average of the sample sequence, while Ensemble average is statistical mean.

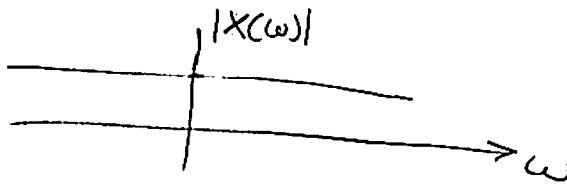
$X(t_n)$ is R.V.



(5) white Noise:

this is a R.P. whose power spectral density is constant. i.e. power contained in a frequency bandwidth B is the same regardless of where this bandwidth is centered.

"flat" spectrum implies $X(t)$ is white noise process.



The above is a description in the frequency domain.

In the time domain, $\Phi_{XX}(m) = \delta(m)$. i.e.

the autocorrelation is nonzero only if the interval is zero. i.e. $X(t)$ only correlates with itself at zero time delay. So all R.V. that belong to a white noise process are uncorrelated with each other if time interval is nonzero.

(6) Ergodic Process:

This is a R.P. where statistics taken from the time samples are the same as statistics taken from Ensembles.

for example. we say a process is Ergodic in the mean, then

$$E\{X(t)\} = \langle X(t) \rangle$$

↓ ↓
 Statistical sample. time average.
 expected value of mean of a sample (or
 R.V. time series)

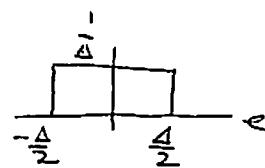
The above equality is in the limit, i.e. as the time series length increases. and the statistical mean is when the Number of time series increases as well.

#3

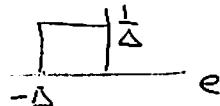
$$y(n) = Q[x(n)] = x(n) + e(n) \rightarrow \text{quantization Error}$$

$e(n)$ is white noise.

Pdf for rounding is uniform



Pdf for truncation is



- a) Find mean and Variance due to rounding
 b) " " " " " " " " truncation.

Answer

$$a) m_e = \int_{-\frac{\Delta}{2}}^{\frac{\Delta}{2}} e \cdot f(e) de = \int_{-\frac{\Delta}{2}}^{\frac{\Delta}{2}} \frac{1}{\Delta} de = \frac{1}{\Delta} \left(\frac{e^2}{2} \right) \Big|_{-\frac{\Delta}{2}}^{\frac{\Delta}{2}}$$

$$= \frac{1}{2\Delta} \left[\left(\frac{\Delta}{2}\right)^2 - \left(-\frac{\Delta}{2}\right)^2 \right] = \frac{1}{2\Delta} (0) = \boxed{0}$$

$$\begin{aligned} E[e^2] &= \int_{-\frac{\Delta}{2}}^{\frac{\Delta}{2}} e^2 f(e) de = \frac{1}{\Delta} \int_{-\frac{\Delta}{2}}^{\frac{\Delta}{2}} e^2 de = \frac{1}{\Delta} \left(\frac{e^3}{3} \right) \Big|_{-\frac{\Delta}{2}}^{\frac{\Delta}{2}} \\ &= \frac{1}{3\Delta} \left[\left(\frac{\Delta}{2}\right)^3 - \left(-\frac{\Delta}{2}\right)^3 \right] = \frac{1}{3\Delta} \left[\frac{\Delta^3}{8} + \frac{\Delta^3}{8} \right] = \frac{1}{3\Delta} \left[\frac{\Delta^3}{4} \right] \\ &= \boxed{\frac{\Delta^2}{12}} \end{aligned}$$

$$\text{so } \sigma^2 = E[e^2] - (E[e])^2 = \frac{\Delta^2}{12} - 0^2 = \boxed{\frac{\Delta^2}{12}}$$

$$\begin{aligned} b) m_e &= \int_{-\Delta}^0 e f(e) de = \int_{-\Delta}^0 e \frac{1}{\Delta} de = \frac{1}{\Delta} \left(\frac{e^2}{2} \right) \Big|_{-\Delta}^0 = \frac{1}{\Delta} (0^2 - (-\Delta)^2) \\ &= \frac{1}{2\Delta} (0 - \Delta^2) = \boxed{-\frac{\Delta}{2}} \end{aligned}$$

$$\begin{aligned} E[e^2] &= \int_{-\Delta}^0 e^2 f(e) de = \int_{-\Delta}^0 e^2 \frac{1}{\Delta} de = \frac{1}{\Delta} \left[\frac{e^3}{3} \right] \Big|_{-\Delta}^0 \\ &= \frac{1}{3\Delta} [0^3 - (-\Delta)^3] = \boxed{\frac{\Delta^2}{3}} \end{aligned}$$

$$\text{so } \sigma^2 = E[e^2] - (E[e])^2 = \frac{\Delta^2}{3} - \left(-\frac{\Delta}{2}\right)^2 = \frac{\Delta^2}{3} - \frac{\Delta^2}{4} = \frac{4\Delta^2 - 3\Delta^2}{12} = \boxed{\frac{\Delta^2}{12}}$$

4 let $e(n)$ white Noise sequence. Let $s(n)$ uncorrelated sequence to $e(n)$. Show that $y(n) = s(n)e(n)$ is white. i.e $E[y(n)y(n+m)] = A \delta(m)$.

Answer

$$E[y(n)y(n+m)] = E[s(n)e(n)s(n+m)e(n+m)] \\ = E[s(n)s(n+m)e(n)e(n+m)]$$

Since $e(n)$ and $s(n)$ are uncorrelated, hence independent, then we can write the above as

$$= E[s(n)s(n+m)] E[e(n)e(n+m)]$$

but $e(n)$ is white. hence $\phi_{ee}^{(n,m)} = E[e(n)e(n+m)] = \boxed{\delta(m)}$ by definition of white signal.

hence $\phi_{yy}^{(n,m)} = E[s(n)s(n+m)] \boxed{\delta(m)}$.

Now, when $m=0$, $\phi_{yy}^{(n,m)} = E[s(n)s(n)] \cdot 1$.

since $s(n)$ is uncorrelated with white Noise, then $m_s = 0$
since $s(n)$ is also white.

hence $E[s^2(n)] = \text{Total average power in } s(n) \\ = A \text{ some constant.}$

hence when $m=0$, $\phi_{yy}^{(n,m)} = A$

when $m \neq 0$ $\phi_{yy}^{(n,m)} = E[s(n)s(n+m)] \cdot 0 \\ = 0$

Therefore $\boxed{\phi_{yy}^{(n,m)} = A \delta(m)}$

since $\phi_{yy}^{(n,m)}$ is function of only m , it is white signal.

#6 Consider 2 real stationary random processes $\{X_n\}$ and $\{Y_n\}$, with mean m_x, m_y , and variance σ_x^2, σ_y^2 .

(a) $\gamma_{xx}(m)$. This is auto covariance.

$$\begin{aligned}\gamma_{xx}(m) &= E\{(x(n)-m_x)(x^{*}(n+m)-m_x^{*})\} \\ &= E\{x(n)x^{*}(n+m) - m_x x(n) - m_x x^{*}(n+m) + m_x^2\} \\ &= E\{x(n)x^{*}(n+m)\} - m_x E\{x(n)\} - m_x E\{x^{*}(n+m)\} \\ &\quad + m_x^2. \\ &= \phi_{xx}(n, n+m) - m_x^2 - m_x E\{x^{*}(n+m)\} + m_x^2 \\ &= \phi_{xx}(n, n+m) - m_x E\{x^{*}(n+m)\}.\end{aligned}$$

but $\{X_n\}$ is stationary, so its statistics do not change with shift of time origin. hence $E\{x^{*}(n+m)\} = E\{x^{*}(n)\} = m_x$.

so above becomes

$$\gamma_{xx}(m) = \phi_{xx}(n, n+m) - m_x^2.$$

but $\phi_{xx}(n, n+m) = \phi_{xx}(m)$ since stationary hence

$$\boxed{\gamma_{xx}(m) = \phi_{xx}(m) - m_x^2}$$

$$\begin{aligned}\gamma_{xy}(m) &= E[(x(n)-m_x)(y^{*}(n+m)-m_y^{*})] \\ &= E[x(n)y^{*}(n+m) - m_y x(n) - m_x y^{*}(n+m) + m_y m_x] \\ &= E\{x(n)y^{*}(n+m)\} - m_y E\{x(n)\} - m_x E\{y^{*}(n+m)\} + m_y m_x\end{aligned}$$

but due to stationarity, $E\{y^{*}(n+m)\} = m_y$. so above becomes

$$\begin{aligned}&= E\{x(n)y^{*}(n+m)\} - m_y m_x - m_x m_y + m_y m_x \\ &= E\{x(n)y^{*}(n+m)\} - m_y m_x.\end{aligned}$$

but $E\{x(n)y^{*}(n+m)\} = \phi_{xy}(m)$ since stationary

$$\therefore \boxed{\gamma_{xy}(m) = \phi_{xy}(m) - m_y m_x} \rightarrow$$

(6)

$$(b) \quad \Phi_{xx}(0) = E\{x(n)x^*(n+m)\}$$

but $m=0$. hence

$$\Phi_{xx}(0) = E\{x(n)x^*(n)\} = E\{x^2(n)\}$$

= mean square.

$$\gamma_{xx}(0) = E\{(x(n)-m_x)(x^*(n+m)-m_x^*)\}$$

but $m=0$ \Rightarrow

$$\gamma_{xx}(0) = E\{(x(n)-m_x)(x^*(n)-m_x^*)\}$$

$$= E\{x^2(n) - x(n)m_x - m_x x^*(n) + m_x^2\}$$

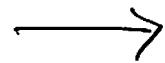
$$= E\{x^2(n)\} - m_x E\{x(n)\} - m_x E\{x^*(n)\} + m_x^2$$

$$= E\{x^2(n)\} - m_x^2 - m_x^2 + m_x^2$$

$$= E\{x^2(n)\} - m_x^2$$

but this is the definition of σ_x^2 . hence

$\gamma_{xx}(0) = \sigma_x^2$



$$(C) \quad \Phi_{xx}(m) = E\{x(n)x^*(n+m)\} = E\{x_{n+m}^*x_n\} = (E\{x_{n+m}x_n^*\})^* \quad (7)$$

$$= \Phi_{xx}^*(-m)$$

if process is real, then $\Phi_{xx}^*(-m) = \Phi_{xx}(-m)$.

$$\text{i.e. } \Phi_{xx}(m) = \Phi_{xx}^*(-m)$$

$$\begin{aligned} \gamma_{xx}(m) &= E\{(x(n)-m_x)(x^*(n+m)-m_x^*)\} \\ &= \Phi_{xx}(m) - m_x m_x^* \quad (\text{from part (a)}). \quad (1) \\ &= \Phi_{xx}^*(-m) - m_x m_x^* \quad (\text{using result above}). \\ &= (E\{x_{n+m}x_n^*\})^* - m_x m_x^* \\ &= E\{x_{n+m}^*x_n\} - m_x m_x^* \\ &= (E\{x_{n+m}x_n^*\} - m_x^* m_x)^* \\ &= \gamma_{xx}^*(-m) \end{aligned}$$

if Real process, then $\gamma_{xx}^*(-m) = \gamma_{xx}(-m) \Rightarrow \boxed{\gamma_{xx}(m) = \gamma_{xx}(-m)}$

$$\begin{aligned} \cancel{\Phi_{xy}(m)} &= E\{(x(n)-m_x)(y(n+m)-m_y)\} \\ &= E\{x(n)y(n+m) - m_y x(n) - m_x y(n+m) + m_x m_y\} \\ &= E\{x(n)y(n+m)\} - m_y m_x - m_x m_y + m_x m_y \\ &\quad - E\{x(n)y(n+m)\} - m_x m_y \end{aligned}$$

$$\begin{aligned} \text{But } \Phi_{yx}^*(-m) &= E\{(y(n)-m_y)(x(n-m)-m_x)\} \\ &= E\{y(n)x(n-m)\} - m_x m_y - m_y m_x + m_y m_x \\ &= E\{y(n)x(n-m)\} - m_x m_y \end{aligned}$$

Since sequences $x(n)$ and $y(n)$ are real, then $\Phi_{yx}^*(-m) = \Phi_{yx}(-m)$.

$$\therefore \cancel{\Phi_{yx}^*(-m)} = E\{x(n-m)y(n)\} - m_x m_y \rightarrow$$

part (c) cont.

Show that $\Phi_{xy}(m) = \Phi_{yx}^*(-m)$.

$$\Phi_{xy}(m) = E\{x_n y_{n+m}^*\} = E\{y_{n+m}^* x_n\} = (E\{y_{n+m} x_n^*\})^*$$
$$= \Phi_{yx}^*(-m)$$

Show that $\gamma_{xy}(m) = \gamma_{yx}^*(-m)$

$$\gamma_{xy}(m) = E\{(x_n - m_x)(y_{n+m}^* - m_y^*)\}$$
$$= E\{(y_{n+m}^* - m_y^*)(x_n - m_x)\}$$
$$= (E\{(y_{n+m} - m_y)(x_n^* - m_x^*)\})^*$$
$$= \gamma_{yx}^*(-m)$$

(9)

part (d)

$$\text{show that } |\phi_{xy}(n)| \leq \sqrt{\phi_{xx}(0) \phi_{yy}(0)}$$

$$\phi_{xy}(n) = E\{x_n y_{n+m}^*\}$$

$$\phi_{xx}(0) = E\{x_n^2\}$$

$$\phi_{yy}(0) = E\{y_n^2\}.$$

we did this in class as follows:

$$0 \leq E\{(x_n + a y_{n+m})^2\} = E\{x_n^2 + a^2 y_{n+m}^2 + 2ax_n y_{n+m}\}$$

$$= E(x_n^2) + a^2 E(y_{n+m}^2) + 2a E(x_n y_{n+m})$$

$$= \phi_{xx}(0) + a^2 \phi_{yy}(0) + 2a \phi_{xy}(n) \quad (= Ax^2 + Bx + C)$$

This is a quadratic equation that is ≥ 0 always.
hence can't have 2 real roots i.e.
discriminant ≤ 0 . i.e.

$$\text{where } A = \phi_{yy}(0), B = 2\phi_{xy}(n), C = \phi_{xx}(0).$$

$$\text{but discriminant is } B^2 - 4AC$$

$$\text{so } 4\phi_{xy}^2(n) - 4\phi_{yy}(0)\phi_{xx}(0) \leq 0.$$

i.e.

$$\phi_{xy}^2(n) \leq \phi_{yy}(0) \phi_{xx}(0)$$

i.e.

$$|\phi_{xy}(n)| \leq \sqrt{\phi_{yy}(0) \phi_{xx}(0)}$$