

HW 3
EGEE 518 Digital Signal Processing I
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1 my solution

①

Definitions

② auto correlation $R_{xx}(n, n+m)$: Measures the similarity of R.P. $X(t)$ at time n and $X(t)$ at later time $n+m$.

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

③ stationary process.
This is a random process whose statistics do not change with shift in time origin.

④ 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

⑤ 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:

②

- 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.



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. whose 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.
expected value of
R.V.

↓
time average..
mean of a sample (or
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.

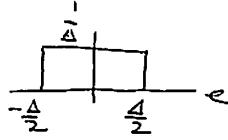
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(3)

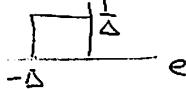
$$y(n) = Q[x(n)] = x(n) + e(n) \xrightarrow{\text{quantization Error}}$$

$e(n)$ is white noise.

Pdf for rounding is uniform



Pdf for truncation is



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

Answer

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

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

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

$$= \frac{1}{3\Delta} \left[\left(\frac{\Delta}{2}\right)^3 - \left(-\frac{\Delta}{2}\right)^3 \right] = \frac{1}{3\Delta} \left[\frac{\Delta^3}{8} + \frac{\Delta^3}{8} \right] = \frac{1}{3\Delta} \left[\frac{\Delta^3}{4} \right]$$

$$= \boxed{\frac{\Delta^2}{12}}$$

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

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

$$= \frac{1}{2\Delta} (-\Delta^2) = \boxed{-\frac{\Delta}{2}}$$

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

$$= \frac{1}{3\Delta} [0^3 - (-\Delta)^3] = \boxed{\frac{\Delta^2}{3}}$$

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

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

$$\begin{aligned} E[y(n)y(n+m)] &= E[s(n)e(n)s(n+m)e(n+m)] \\ &= E[s(n)s(n+m) E[e(n)e(n+m)]] \end{aligned}$$

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 $E[e(n)e(n+m)] = \boxed{\delta(m)}$ by definition of white signal.

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

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

since $s(n)$ is uncorrelated with white Noise, then $E[s(n)s(n)] = 0$ 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 autocorrelation.

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

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

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

$$\begin{aligned}\gamma_{xy}(m) &= E[(x(n)-m_x)(y^{*(n+m)}-m_y^*)] \\ &= E[x(n)y^{*(n+m)} - m_y x(n) - m_x y^{*(n+m)} + m_y m_x] \\ &= E\{x(n)y^{*(n+m)}\} - m_y E\{x(n)\} - m_x E\{y^{*(n+m)}\} + m_y m_x \\ \text{but due to stationarity, } E\{y^{*(n+m)}\} &= m_y. \text{ so above becomes} \\ &= E\{x(n)y^{*(n+m)}\} - m_y m_x - m_x m_y + m_y m_x \\ &= E\{x(n)y^{*(n+m)}\} - m_y m_x.\end{aligned}$$

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

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

$$(b) \quad \Phi_{xx}(0) = E\{x(n)x^*(n+m)\} \quad (6)$$

but $m=0$. hence

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

= mean square.

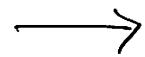
$$\gamma_{xx}(0) = E\{(x(n)-m_x)(x^*(n+m)-m_x^*)\}$$

but $m=0$ \Rightarrow

$$\begin{aligned} \gamma_{xx}(0) &= E\{(x(n)-m_x)(x^*(n)-m_x^*)\} \\ &= E\{x^2(n) - x(n)m_x - m_x x^*(n) + m_x^2\} \\ &= E\{x^2(n)\} - m_x E\{x(n)\} - m_x E\{x^*(n)\} + m_x^2 \\ &= E\{x^2(n)\} - m_x^2 - m_x^2 + m_x^2 \\ &= E\{x^2(n)\} - m_x^2 \end{aligned}$$

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 $\gamma_{xx}^*(-m) = \gamma_{xx}(-m) \Rightarrow \boxed{\gamma_{xx}(m) = \gamma_{xx}(-m)}$

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

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

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

part (c) Cont.

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

$$\begin{aligned} \Phi_{xy}(m) &= E\{x_n y_{n+m}^*\} = E\{\bar{y}_{n+m}^* x_n\} = (E\{\bar{y}_{n+m} x_n^*\})^* \\ &= \Phi_{yx}^*(-m) \end{aligned}$$

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

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

(

part (d)

(9)

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

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

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

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

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.

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

but discriminant is $B^2 - 4AC$

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

i.e.

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

i.e.

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

2 key solution

H.W. #3 Sol.

- ① a) Autocorrelation sequence : $\phi_{xx}(n, m)$ is defined by

$$\phi_{xx}(n, m) = E \{ X_n X_m^* \} = \iint_{-\infty}^{\infty} x_n x_m^* P_{X_n X_m}(x_n, n, x_m, m) dx_n dx_m$$

- b) A random process $\{X_n\}$ is a stationary process if its statistics are not affected by a shift in the time origin. i.e., X_n and X_m have the same statistics for all n and m
- c) A stationary random process in the wide sense mean
- (i) The mean is constant
 - (ii) the autocorrelation (2nd order statistic) depend only on the time difference between the random variables
- d) Time average of a random process $\{X_n\}$ is defined as

$$\langle X_n \rangle = \lim_{N \rightarrow \infty} \frac{1}{2N+1} \sum_{n=-N}^{N} X_n$$

Ensemble average of a random process $\{X_n\}$ is defined as

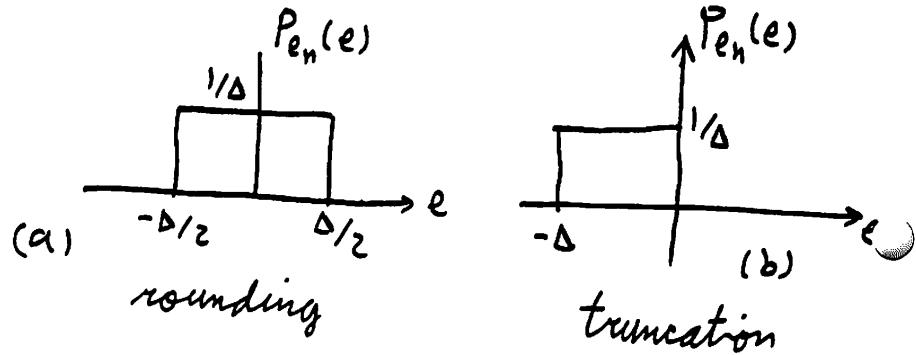
$$m_{X_n} = E\{X_n\} = \int_{-\infty}^{\infty} x P_{X_n}(x, n) dx$$

e) White noise is a random process in which all the random variables are independent with zero mean.

$$\Phi_{xx}(m) = \sigma_x^2 \delta(m)$$

f) A random process for which the time averages equal the ensemble averages is called an ergodic process.

② 8.3



Prob. distribution

a) Mean & Variance, rounding

$$m_e = \int_{-\infty}^{\infty} e P_{e_n}(e) de = \int_{-\Delta/2}^{\Delta/2} e \frac{1}{\Delta} de = \frac{1}{\Delta} \left[\frac{e^2}{2} \right]_{-\Delta/2}^{\Delta/2} = 0$$

$$\begin{aligned} \sigma_e^2 &= E\{e_n^2\} = \int_{-\infty}^{\infty} e^2 P_{e_n}(e) de = \frac{1}{\Delta} \int_{-\Delta/2}^{\Delta/2} e^2 de \\ &= \frac{e^3}{3\Delta} \Big|_{-\Delta/2}^{\Delta/2} = \frac{1}{3\Delta} 2 \frac{\Delta^3}{8} = \frac{\Delta^2}{12} \end{aligned}$$

b) For truncation

$$m_e = \frac{1}{\Delta} \int_{-\Delta}^0 e \, de = \frac{1}{\Delta} \frac{e^2}{2} \Big|_{-\Delta}^0 = -\frac{\Delta^2}{2}$$

$$\begin{aligned} \overline{e^2} &= E \left\{ (e_n + \frac{\Delta}{2})^2 \right\} = E \{e_n^2\} + \frac{\Delta^2}{4} + 2 \frac{\Delta}{2} E \{e_n\} \\ &= E \{e_n^2\} + \frac{\Delta^2}{4} - \frac{\Delta^2}{2} = \underline{E \{e_n^2\} - \frac{\Delta^2}{4}} \end{aligned}$$

$$\overline{e^2} = \frac{1}{\Delta} \int_{-\Delta}^0 e^2 \, de - \frac{\Delta^2}{4} = \frac{1}{\Delta} \frac{e^3}{3} \Big|_{-\Delta}^0 - \frac{\Delta^2}{4} = \frac{\Delta^2}{12}$$

③ 8.4 $e(n)$: white noise req.
 $s(n)$: uncorrelated with $e(n)$

show $y(n) = s(n)e(n)$ is white; i.e.

$$E \{ y(n) y(n+m) \} = A \delta(m)$$

Sol. $\underbrace{e(n)}$ white $\Rightarrow E \{ e(n) e(n+m) \} = \overline{e^2} \delta(m)$

$$\begin{cases} \text{white} & E \{ e(n) e(n+m) \} = \overline{e^2} \delta(m) \\ \text{Uncorrelated} & E \{ e(n) y(m) \} = E \{ e(n) \} E \{ y(m) \} \end{cases}$$

$$E \{ y(n) y(n+m) \} = E \{ s(n) e(n) s(n+m) e(n+m) \}$$

assume
 $s(n)$ is WSS
or white noise

$$= E \{ s(n) s(n+m) e(n) e(n+m) \}$$

$$= E \{ s(n) s(n+m) \} E \{ e(n) e(n+m) \}$$

$$= E \{ s(n) s(n+m) \} \overline{e^2} \delta(m)$$

$$= \overline{s^2} \overline{e^2} \delta(m)$$

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8.6 Consider the two real stationary random processes $\{x_n\}$ and $\{y_n\}$, with means m_x and m_y and variances σ_x^2 and σ_y^2 .

Show the following

$$(a) \underline{\delta_{xx}(m)} = \underline{\phi_{xx}(m) - m_x^2} \quad \& \quad \underline{\delta_{xy}(m)} = \underline{\phi_{xy}(m) - m_x - m_y}$$

$$\begin{aligned} \underline{\delta_{xx}(m)} &= E[(x_n - m_x)(x_{n+m} - m_x)] \\ &= E[x_n x_{n+m}] - m_x E[x_{n+m}] - m_x E[x_n] + m_x m_x \\ &= \underline{\phi_{xx}(m) - m_x m_x - m_x m_x + m_x m_x} \\ &= \underline{\phi_{xx}(m) - m_x^2} \end{aligned}$$

$$\begin{aligned} \underline{\delta_{xy}(m)} &= E[(x_n - m_x)(y_{n+m} - m_y)] \\ &= E[x_n y_{n+m}] - m_x m_y - m_y m_x + m_x m_y \\ &= \underline{\phi_{xy}(m) - m_x m_y} \end{aligned}$$

$$(b) \underline{\phi_{xx}(0)} = \text{mean square} \quad \& \quad \underline{\delta_{xx}(0)} = \underline{\sigma_x^2}$$

$$\underline{\phi_{xx}(m)} = E[x_n x_{n+m}] =$$

$$\underline{\phi_{xx}(0)} = E[x_n x_n] = \text{mean square}$$

$$\underline{\delta_{xx}(m)} = E[(x_n - m_x)(x_{n+m} - m_x)]$$

$$\underline{\delta_{xx}(0)} = E[(x_n - m_x)^2] = \underline{\sigma_x^2}$$

$$(c) \underline{\phi_{xx}(m)} = \underline{\phi_{xx}(-m)}$$

$$\underline{\phi_{xx}(-m)} = (E[x_n x_{n-m}])$$

$$\text{let } n' = n - m$$

$$\begin{aligned} \underline{\phi_{xx}(-m)} &= (E[x_{n'} x_m x_{n'}]) = E[x_{n'} x_{n'+m}] \\ &= \underline{\phi_{xx}(m)} \end{aligned}$$

$$\underline{\delta_{xx}(m)} = \underline{\delta_{xx}(-m)}$$

$$\begin{aligned} \underline{\delta_{xx}(-m)} &= (E[(x_n - m_x)(x_{n-m} - m_x)]) \\ &= (E[(x_{n'+m} - m_x)(x_{n'} - m_x)]) \\ &= E[(x_{n'} - m_x)(x_{n'+m} - m_x)] \\ &= \underline{\delta_{xx}(m)} \end{aligned}$$

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$$\begin{aligned}\frac{\phi_{xy}(m)}{\phi_{yx}(-m)} &= \frac{\phi_{yx}(-m)}{(E[(y_n - m_y)(x_{n-m} - m_x)])} \\ &= (E[(y_{n+m} - m_y)(x_{n+m} - m_x)]) \\ &= E[(x_{n+m} - m_x)(y_{n+m} - m_y)] \\ &= \phi_{xy}(m)\end{aligned}$$

$$\begin{aligned}\frac{\delta_{xy}(m)}{\delta_{yx}(-m)} &= \frac{\delta_{yx}(-m)}{(E[(y_n - m_y)(x_{n-m} - m_x)])} \\ &= (E[(y_{n+m} - m_y)(x_{n+m} - m_x)]) \\ &= E[(x_{n+m} - m_x)(y_{n+m} - m_y)] \\ &= \delta_{xy}(m).\end{aligned}$$

(d) Consider the inequality

$$E\left\{\left(\frac{x_n}{(E[x_n^2])^{1/2}} - \frac{y_{n+m}}{(E[y_{n+m}^2])^{1/2}}\right)^2\right\} \geq 0$$

This is true since the quantity inside the brackets is > 0 for all m and n .

Now

$$E\left[\frac{x_n^2}{E[x_n^2]}\right] + E\left[\frac{y_{n+m}^2}{E[y_{n+m}^2]}\right] - 2\frac{E[x_n y_{n+m}]}{(E[x_n^2])^{1/2} (E[y_{n+m}^2])^{1/2}} \geq 0$$

This can be written as

$$\frac{\phi_{xx}(0)}{\phi_{xx}(0)} + \frac{\phi_{yy}(0)}{\phi_{yy}(0)} - \frac{2\phi_{xy}(m)}{\phi_{xx}^{1/2}(0) \phi_{yy}^{1/2}(0)} \geq 0$$

$$\frac{\phi_{xy}(m)}{\phi_{xx}^{1/2}(0) \phi_{yy}^{1/2}(0)} \leq 1 \Rightarrow [\phi_{xx}(0) \phi_{yy}(0)]^{1/2} \geq |\phi_{xy}(m)|$$

Now if we replace x_n by $(x_n - m_x)$ and y_{n+m} by $(y_{n+m} - m_y)$ in the inequality we can manipulate it in the same way to get

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$$[\gamma_{xx}(0) \gamma_{yy}(0)]^{1/2} \geq \gamma_{xy}(m)$$

Letting $y_m = x_m$ we can specialize these inequalities to

$$\begin{aligned}\phi_{yy}(0) &\geq \phi_{xx}(m) \\ \gamma_{yy}(0) &\geq \gamma_{xx}(m)\end{aligned}$$

(e) Let $y_m = x_{m-m}$

$$\begin{aligned}\underline{\phi_{yy}(m)} &= E[y_m y_{m+m}] \\ &= E[x_{m-m} x_{m+m-m}] \\ &= \underline{\phi_{xx}(m)}\end{aligned}$$

Obviously $\underline{\gamma_{yy}(m)} = \underline{\gamma_{xx}(m)}$ for the same reasons.

(f) Let $\gamma_{xx}(m) \longleftrightarrow \Gamma_{xx}(z)$

$\gamma_{xy}(m) \longleftrightarrow \Gamma_{xy}(z)$

$$\Gamma_{xx}(z) \triangleq \sum_m \gamma_{xx}(m) z^{-m} \Rightarrow (1) \quad \gamma_{xx}(m) = \frac{1}{2\pi j} \oint_c \Gamma_{xx}(z) z^{m-1} dz$$

$$\gamma_{xx}(0) = \underline{\Gamma_{xx}^2} = \frac{1}{2\pi j} \oint_c \Gamma_{xx}(z) z^{-1} dz$$

(2) We have shown that $\gamma_{xx}(m) = \gamma_{xx}(-m)$

$$\text{Therefore } \Gamma_{xx}(z) = \sum_{m=-\infty}^{\infty} \gamma_{xx}(m) z^{-m}$$

$$\underline{\Gamma_{xx}^{-1}(z)} = \sum_{m=-\infty}^{\infty} \gamma_{xx}(m) z^m = \sum_{p=-\infty}^{\infty} \gamma_{xx}(-p) z^p$$

$$= \sum_{m=-\infty}^{\infty} \gamma_{xx}(m) z^m = \underline{\Gamma_{xx}(z)}$$

$$p \rightarrow m \Rightarrow$$

$$\text{use } \gamma_{xy}(m) = \gamma_{yx}^*(-m)$$

$$\begin{aligned}
 \Gamma_{xy}(z) &= \sum_{m=-\infty}^{\infty} \gamma_{xy}(m) z^{-m} = \sum_{m=-\infty}^{\infty} \gamma_{yx}^*(-m) z^{-m} \\
 &= \left(\sum_{\ell=-\infty}^{\infty} \gamma_{yx}(\ell) z^{*\ell} \right)^* \\
 &= \left(\sum_{\ell=-\infty}^{\infty} \gamma_{yx}(\ell) (z^{*-1})^{-\ell} \right)^* = \Gamma_{yx}^*(1/z^*)
 \end{aligned}$$