

Statistical Signal Processing
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Lecture - 31
Solution to Review Assignment 3

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Q.1 Given stationary observations $Y(n)$, $n \in \mathbb{Z}$, a linear estimator of $X(n)$ is given by

$$\hat{X}(n) = a_1 Y(n-1) + a_0 Y(n) + a_{-1} Y(n+1)$$

Use the orthogonality condition to derive the WH equation and the corresponding MMSE.

Handwritten notes:

$$\hat{X}(n) = a_1 Y(n-1) + a_0 Y(n) + a_{-1} Y(n+1)$$

$$e(n) = X(n) - a_1 Y(n-1) - a_0 Y(n) - a_{-1} Y(n+1)$$

Error is orthogonal to data $E\{e(n)Y(n-j)} = 0, j = -1, 0, 1$

(I) $E\{X(n) - a_1 Y(n-1) - a_0 Y(n) - a_{-1} Y(n+1) Y(n)\} = 0$

$$\Rightarrow a_1 R_Y(1) + a_0 R_Y(0) + a_{-1} R_Y(-1) = R_{XY}(0)$$

(II) $E\{X(n) - a_1 Y(n-1) - a_0 Y(n) - a_{-1} Y(n+1) Y(n-1)\} = 0$

$$\Rightarrow a_1 R_Y(0) + a_0 R_Y(1) + a_{-1} R_Y(2) = R_{XY}(1)$$

(III) $E\{X(n) - a_1 Y(n-1) - a_0 Y(n) - a_{-1} Y(n+1) Y(n+1)\} = 0$

$$\Rightarrow a_1 R_Y(2) + a_0 R_Y(1) + a_{-1} R_Y(0) = R_{XY}(2)$$

with equations

Hello students. Welcome to this session on solution to review assignment 3. Here, we will solve some problems of Wiener filter. First one is given a linear estimator of X_n is given by $\hat{X}_n = a_1 Y_{n-1} + a_0 Y_n + a_{-1} Y_{n+1}$. Use the orthogonality condition to derive the Wiener-Hopf equation and the corresponding minimum mean square error. Signal is WSS and $\hat{X}_n$ is $a_1 Y_{n-1} + a_0 Y_n + a_{-1} Y_{n+1}$ filtered data is also used.

Therefore, error e_n will be $= x_n - a_1 Y_{n-1} - a_0 Y_n - a_{-1} Y_{n+1}$. Now the orthogonality condition is error is orthogonal to data. So we will get that orthogonality condition that means $E\{e_n Y_{n-j}\} = 0$ for $j = -1, 0, 1$ because when $j = -1$ this is Y_{n+1} $j = 0$ it will be Y_n and $j = 1$ it will be Y_{n-1} . So that way 3 equations we will get.

Therefore, we will have $E\{x_n - a_1 Y_{n-1} - a_0 Y_n - a_{-1} Y_{n+1} Y_{n+1}\} = 0$ that is number one equation, equation 1 this is one equation. So that way we will get now imply that we will first compute this one so E of this one will be Y_{n-1}

into y of $n + 1$ so that way it will be R_y of 2. So that way a_1 we take these values to the right hand side.

So we will consider this part first a_1 into $R_y n - 1 - n - 1$ so that way it will be R_y of 2 because of this stationarity assumption and similarly this term will be a_0 into Y_n into y_{n+1} expected value of that, that will be R_y of 1 and this term will be $+ a - 1$ times E of y_{n+1} into y_{n+1} into y_{n+1} that will be equal to R_y of 0. So whole will be equal to now E of x_n into y_{n+1} so that way it will be $R_{xy} n - n - 1 R_{xy}$ of -1 .

So this is equation 1 then second equation we will get 2 equation 2 E of $x_n - a_1$ into $Y_{n-1} - a_0$ into $y_n - a - 1$ into y_{n+1} into $y_n = 0$ that is corresponding to $j = 0$. So from this we will consider this first part so we will get a_1 times E of Y_{n-1} into y_n so that way it will R_y of 1 + next we will consider a_0 times $a_0 y_n$ into $y_n R_y$ of 0. Then we will consider this one y_{n+1} into y_{n+1} into y_n so that will be equal to $+ a - 1$ into R_y of 1.

E of y_{n+1} into y_n that will be equal to R_y of 1 that must be $= E$ of x_n into y_n that equal to R_{xy} of 0 so this is the second equation. Third equation we will get that is E of error, error is $x_n - a_1 Y_{n-1} - a_0$ into $Y_n - a - 1$ into y_{n+1} into now that equal to 1 so $y_n - 1 = 0$. So from that what we will get we will consider this one first so that way a_1 times E of y_{n-1} into $y_n - 1$ that way it will be R_y of 0 + a_0 times E of Y_n into $y_n - 1$ so that it will be R_y of 1.

And this term will be $a - 1$ into E of y_{n+1} into $y_n - 1$ so that way this will be R_y of 2. So that will be equal to now $x_n y_n - 1 E$ of x_n into $y_n - 1$ that will be R_{xy} of 1. So that way we have 3 equations. First one is this equation second one is this equation and third one is this equation these are the Wiener-Hopf equations WH equations or normal equations. Next is use orthogonal to derive the corresponding minimum mean square error.

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$$\begin{aligned}
 \text{MMSE} &= E \left(x^{(n)} - a_1 y^{(n-1)} - a_0 y^{(n)} - a_{-1} y^{(n+1)} \right) \left(x^{(n)} - a_1 y^{(n-1)} - a_0 y^{(n)} - a_{-1} y^{(n+1)} \right) \\
 &= E \left(x^{(n)} - a_1 y^{(n-1)} - a_0 y^{(n)} - a_{-1} y^{(n+1)} \right) x^{(n)} \\
 &= R_x(0) - a_1 R_{xy}(1) - a_0 R_{xy}(0) - a_{-1} R_{xy}(-1)
 \end{aligned}$$

So here also we can use the orthogonality that is minimum mean square error $E = E$ of $x_n - a_1 y_{n-1} - a_0 y_n - a_{-1} y_{n+1}$ into y_{n+1} so this is the error into error square actually. So this we can write like this that is $x_n - a_1 y_{n-1} - a_0 y_n - a_{-1} y_{n+1}$ into y_{n+1} . So this is the expression now we will use the orthogonality principle this is the error, error is orthogonal to data so error is orthogonal to y_{n-1} , error is orthogonal to y_n , error is orthogonal to y_{n+1} because these are the data.

So that way what we will have this contribution of this part will become 0 so that way we will have E of $x_n - a_1 y_{n-1} - a_0 y_n - a_{-1} y_{n+1}$ into x_n because contribution of this part will be 0 E of e_n into y_{n-1} will be 0 E of e_n into y_n will be 0 E of e_n into y_{n+1} will be equal to 0. So that way we will be left with this quantity only and this equal to x_n into x_n E of x_n into x_n will be R_x of 0 $- a_1 E$ of x_n into y_{n-1} will be R_{xy} of 1 a_0 into E of y_n into x_n that will be equal to R_{xy} of 0 and similarly this one will be E of y_{n+1} into x_n . So that way in terms of R_{xy} it will be $n - n - 1 R_{xy}$ of -1 . So this is the MMSE minimum mean square error.

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Q.2 A random signal $X(n)$ is given by

$$X(n) = 10 \cos\left(\frac{\pi n}{3} + \phi\right)$$

where ϕ is a random variable uniformly distributed in $(0, 2\pi)$. The signal is corrupted by an additive white Gaussian noise $V(n)$ of mean zero and variance 1 to get the observed signal $Y(n)$. Assume $V(n)$ and $X(n)$ to be independent.

- Find the expressions for $R_X(m)$, $R_Y(m)$ and $R_{XY}(m)$
- Find the Wiener-Hopf (W-H) equation for the 2-tap FIR Wiener filter to estimate $X(n)$ from $Y(n)$
- Solve the W-H equation to obtain the filter parameters.
- Obtain the corresponding mean square estimation error.
- Suppose two observations are given as $Y(5) = 11$ and $Y(6) = 6$. Find the output of the filter $\hat{X}(6)$

Let us consider question 2. A random signal X_n is given by $X_n = 10 \cos(\pi n/3 + \phi)$ where ϕ is a random variable uniformly distributed in the interval 0 to 2π . ϕ is uniformly distributed in the interval 0 to 2π . This signal is corrupted by an additive white Gaussian noise V_n of mean zero and variance 1. This variance is 1 variance of V_n is 1 to get the observed signal Y_n .

Assume V_n and X_n to be independent so that X_n and that additive noise part are independent. Find the expressions for R_X of m , R_Y of m and R_{XY} of m . Similarly question B is find the Wiener-Hopf equation for the 2-tap FIR Wiener filter to estimate X_n from Y_n . Part C is solve the Wiener-Hopf equation to obtain the filter parameters. Then part D is obtain the corresponding mean square estimation error. Suppose 2 observations are given as $Y_5 = 11$ and $Y_6 = 6$ find the output of the filter $\hat{X}_6$. So at instance 6 what is the output of the filter.

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$$\begin{aligned}
 x(n) &= 10 \cos(\pi n / 3 + \phi) \\
 \phi &\sim U[0, 2\pi] \\
 R_x(m) &= E[x(n)x(n-m)] = \frac{10^2}{2} \cos(\pi/3 m) \quad m=0, \pm 1, \dots \\
 &\boxed{R_x(m) = 50 \cos(\pi/3 m)} \\
 Y(n) &= X(n) + V(n) \\
 R_Y(m) &= R_X(m) + R_V(m) \\
 \therefore R_Y(m) &= 50 \cos(\pi/3 m) + \delta(m) \\
 R_{XY}(m) &= E[X(n)Y(n-m)] \\
 &= E[X(n)(X(n-m) + V(n-m))] \\
 &= E[X(n)X(n-m)] + E[X(n)V(n-m)] \\
 &= R_X(m) + 0 \\
 \therefore R_{XY}(m) &= R_X(m)
 \end{aligned}$$

To solve this question, we are given $X_n = 10 \cos(\pi/3 n + \phi)$ this is the signal. Now ϕ is uniformly distributed ϕ is uniformly distributed between 0 to 2π . So we have to find out R_X of m . R_X of m will be equal to $E[X(n)X(n-m)]$ (14:27) $n-m$ and if we carry out this expectation operation and as we have shown in an earlier example so this will be simply $10^2 / 2 \cos(\pi/3 m)$ that equal to $50 \cos(\pi/3 m)$ so this is for $m = 0, -1$ etcetera.

And we have to find out R_X of m R_Y of m . Now you are given that $Y_n = X_n + V_n$ so V_n and X_n are independent and in this case we can show that R_Y of m will be equal to R_X of m + R_V of m . How do I show this $E[Y(n)Y(n-m)]$ that is my R_Y of m . So this equal to $E[X(n) + V(n)Y(n-m)]$ will be $E[X(n)X(n-m) + V(n)Y(n-m)]$ and this $X(n)X(n-m)$ if I take the expectation this one will be R_X of m .

Now this is $E[V(n)X(n-m)]$ because noise and signal are independent. Therefore, this will be $E[V(n)]E[X(n-m)]$ but $V(n)$ is zero mean so therefore that will be equal to 0. So because of independent assumption this part will be equal to 0. Similarly, $X(n)V(n-m)$ that will be also equal to 0 because this signal and noise are independent and therefore $V(n)$ of $X(n)V(n-m)$ will be equal to $E[X(n)]E[V(n-m)]$, but $E[V(n-m)] = 0$ therefore this cross term is also equal to 0.

And this part $E[V(n)V(n-m)]$ that will be R_V of m . Therefore, we will have $R_Y(m) = R_X(m) + R_V(m)$ and I know R_X of m that is $50 \cos(\pi/3 m)$ and R_V of m now noise is unity variance zero mean uncorrelated. Therefore, this will be 1 into variance is 1 into $\delta(m)$

where $\delta_m = 1$ for $m = 0$ and 0 otherwise. So this is the value of $R_Y(m)$ then we have to find out $R_{XY}(m)$ will be $= E$ of X_n into y_{n-m} so this $= E$ of X_n into X of $n-m$ + v of $n-m$.

Now signal and noise are independent and also this zero mean therefore we will have this E of x_n into v_{n-m} will be simply $= 0$. So what we will be left with E of x_n into x of $n-m$ + 0 that $= R_X$ of m so therefore R_{XY} of m will be simply R_X of m . So, next part is so we have to now find out the Wiener-Hopf equation for 2-tap FIR Wiener filter. So that way we have found out R_X of m we have found out this is R_X of m R_X of m equal to this, this we have found out.

Similarly, R_Y of m equal to; therefore R_Y of m equal to this, this also we have found out and we have found out R_{XY} of m is m also we have found out. So these are the expression for R_X of m , R_{XY} of m and R_Y of m .

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2-tap Wiener filter (length 2)

$$\hat{x}(n) = h(0)y(n) + h(1)y(n-1)$$

orthogonality $\Rightarrow E[(x(n) - \hat{x}(n))y(n-j)] = 0, j=0, 1$

$$\begin{cases} h(0)R_Y(0) + h(1)R_Y(1) = R_{XY}(0) \\ h(0)R_Y(1) + h(1)R_Y(0) = R_{XY}(1) \end{cases}$$

with equations

$$\begin{bmatrix} R_Y(0) & R_Y(1) \\ R_Y(1) & R_Y(0) \end{bmatrix} \begin{bmatrix} h(0) \\ h(1) \end{bmatrix} = \begin{bmatrix} R_{XY}(0) \\ R_{XY}(1) \end{bmatrix}$$

$$\begin{bmatrix} 5 & 2.5 \\ 2.5 & 5 \end{bmatrix} \begin{bmatrix} h(0) \\ h(1) \end{bmatrix} = \begin{bmatrix} 50 \\ 25 \end{bmatrix}$$

$$\begin{aligned} h(0) &= 0.9742 \\ h(1) &= 0.0127 \end{aligned}$$

$$\text{MMSE} = R_X(0) - h(0)R_{XY}(0) - h(1)R_{XY}(1) = 50 - 0.9742 \times 50 - 0.0127 \times 25 = 0.972$$

Next we have to find out the Wiener-Hopf equation so it is a 2-tap Wiener filter 2-tap Wiener filter this is length-2 Wiener filter where this is length 2. So that therefore estimated signal $\hat{x}_n$ will be $= h$ of 0 into y_n + h of 1 into y_{n-1} this is the filter equation and filter output is the estimated signal and using orthogonality condition E of $x_n - \hat{x}_n$ into $y_n - h_0 y_n - h_1 y_{n-1}$ into $y_{n-j} = 0$ for $j = 0$ and 1.

So this is the condition so from this we will get h_0 into R_Y of this one will give R_Y of for $j = 0$ I will h_0 into R_Y of 0 + h_1 into R_Y of 1 will be $= x_n$ into y_n that is R_{XY} of 0 this is the first equation. Second equation when we put $j = 1$ so that way this one will be h_0 into y_n into y_{n-1}

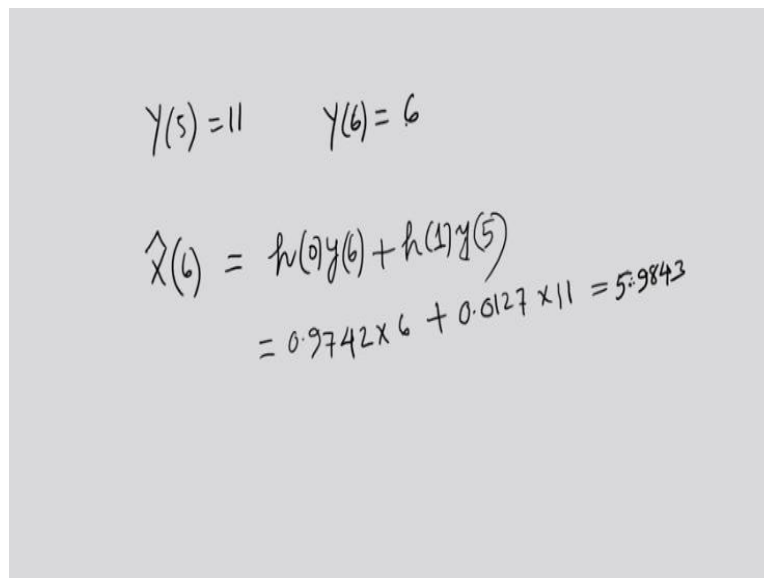
1 expected value so that way it will be R_Y of 1 and similarly this part h_1 into R_Y of 1 and here we will have R_{xY} of 1.

So this two equations we have these are the Wiener-Hopf equations. So we can substitute the values now. So in matrix form also we can write it as R_{Y0} here R_{Y1} here R_{Y1} here R_{Y0} here and then into h_0 h_1 here must be equal to R_{xY} 0 R_{xY} 1 and we can substitute the value so R_{Y0} is from this expression R_{Y0} will be 50 because $\cos$ of 0 will be equal to 1 this is 1 so that way it will be 51 so that way this will be 51.

R_{Y1} will be R_{Y1} will be equal to 50 into $\cos \pi/3$ that will be 25 $\cos$ of $\pi/3$ is half and this is 0 so that way this is 25 here also 25 here 51 and into h_0 h_1 and this side similarly we will have R_x of 0 that is 50 and this is 25. So this is the Wiener-Hopf equation we can directly solve this either two linear equations or by matrix inversion and we can get $h_0 = 0.9742$ and $h_1 = 0.0127$ so these are the filter coefficients.

So we have found out h_0 h_1 so MMSE that is minimum mean square error that is equal to $R_{x0} - h_0$ into $R_{xY0} - h_1$ into R_{xY} 1. So all these data are available R_{x0} is 50 and h_0 we have found out 0.9742 into R_{xY0} R_{xY0} was 50 only $- h_1$ h_1 was 0.0127 and R_{xY} of 1 is 0 that is 25 so if we carry out this calculation this will be 0.972. So we have found out the minimum mean square error. Next we are given $Y_5 = 11$ $Y_6 = 6$ to find the filter output $\hat{X}$ at 6 so we have to estimate the signal at instant 6.

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Handwritten mathematical derivation for the filter output at instant 6:

$$Y(5) = 11 \quad Y(6) = 6$$

$$\hat{X}(6) = h(0)Y(6) + h(1)Y(5)$$

$$= 0.9742 \times 6 + 0.0127 \times 11 = 5.9843$$

So we are given $Y_5 = 11$ and $Y_6 = 6$ so we have to estimate $\hat{X}_6$. So $\hat{X}_6$ that equal to h_0 into y of 6 + h_1 into y of 5. So we can substitute the values so this equal to h_0 is 0.9742 multiplied by y_6 that equal to 6 + h_1 is 0.0127 multiplied by y_5 that is 11. So this we will get as 5.9843 so this is the estimated value of signal at 0.6 so $\hat{X}_6$ is 5.9843 observed value was 6 estimated value is 5.9843.

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Q.3 Assume the observation model $Y(n) = X(n) + V(n)$ where $V(n)$ is a zero-mean white noise with variance 1 and $X(n)$ has an autocorrelation function $R_X(m) = 0.6^{|m|}, m \in \mathbb{Z}$.

- (a) Find the expressions for $S_X(z)$, $S_Y(z)$ and $S_{XY}(z)$
- (b) Find the transfer function of the noncausal IIR Wiener filter to estimate $X(n)$.
- (c) What is the transfer function of the optimal non-causal Wiener filter if $V(n) = 0$ in the model?

Let us go to the next question assume the observation model $Y_n = X_n + V_n$ where V_n is a zero mean white noise with variance 1 and X_n has an autocorrelation function $R_X(m) = 0.6^{|m|}$ to the power mod of m where m belongs to $\mathbb{Z}$ integer. Find the expression for $S_X(z)$, $S_Y(z)$ and $S_{XY}(z)$. Part B is find the transfer function the non-causal IIR Wiener filter to estimate X_n . Part C is what is the transfer function of the optimal non-causal Wiener filter if $V_n = 0$ in the model.

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$$\begin{aligned}
 R_x(m) &= 0.6^{|m|} \\
 S_x(z) &= \sum_{m=-\infty}^{\infty} R_x(m) z^{-m} = \sum_{m=-\infty}^{\infty} 0.6^{|m|} z^{-m} = \sum_{m=-\infty}^{-1} 0.6^{-m} z^{-m} + \sum_{m=0}^{\infty} 0.6^m z^{-m} \\
 &= \sum_{l=1}^{\infty} 0.6^l z^l + \sum_{m=0}^{\infty} 0.6^m z^{-m} \\
 &= \frac{0.6z}{1-0.6z} + \frac{1}{1-0.6z^{-1}} \\
 &= \frac{0.6z}{(1-0.6z)(1-0.6z^{-1})} = \frac{0.64}{(1-0.6z)(1-0.6z^{-1})} \\
 R_y(m) &= R_x(m) + R_v(m) \quad \text{where } R_v(m) = \delta(m) \\
 \therefore S_y(z) &= \frac{0.64}{(1-0.6z)(1-0.6z^{-1})} + 1 = \frac{2 - 0.6(z+z^{-1})}{(1-0.6z)(1-0.6z^{-1})} \\
 R_{xy}(m) &= R_x(m) \\
 \therefore S_{xy}(z) &= S_x(z) = \frac{0.64}{(1-0.6z)(1-0.6z^{-1})}
 \end{aligned}$$

So we will solve this we are given R_x of $m = 0.6$ to the power m R_x of $m = 0.6$ to the power mod of m . So to find out the non-causal Wiener filter transfer function we have to find the Generalized power spectral density. So we will find out $S_X(z)$. $S_X(z)$ that equal to by definition R_X of m into z to the power $-m$ m going from minus infinity to infinity so that way this will be summation m going from minus infinity to plus infinity 0.6 to the power mod of m into z to the power $-m$.

And this we can write as for negative m this will be 0.6 to the power $-m$ so that way 0.6 to the power $-m$ z to the power $-m$ m going from minus infinity to $-1 + 0.6$ to the power m for positive m mod of m means equal to m into z to the power $-m$ m going from 0 to infinity. Now this we can further simplify by putting minus $m = l$ so that this summation can be rewritten as 0.6 to the power l z to the power l l is going from 1 to infinity.

And this is one is summation m going from 0 to infinity 0.6 to the power m z to the power $-m$. These are geometric series provided the common ratio less than 1 we can find out the infinite sum and in the region of convergence we will have the summation like this for this first term will be $6z$ divided by common ratio is $0.6z$ $1 - 0.6z$ and this part is first term is 1 so $1 -$ common ratio is 0.6 into 6 to the power -1 .

So this is the $S_X(z)$ and this we can simplify as $1 - 0.6z$ into $1 - 0.6z$ inverse and here if we multiply by $0.6z$ into $1 - 0.6z$ inverse $+ 1 - 0.6z$. So if simplify then we will get because this $0.6z$ and $-0.6z$ will get cancel $0.6z$ inverse will be equal to -0.36 so that way the result

will be $1 - 0.36$ that is 0.64 divided by $1 - 0.6 z$ into $1 - 0.6 z$ inverse. So we have found out SX of z now signal and noise are uncorrelated.

Therefore, RYm autocorrelation of the output will be equal to Rxm + Rvm v is the white noise. So taking the z transform we will get $S_{Yz} = S_{Xz} + S_{Vz}$. Now this we know this quantity is 1 into δm because variance 1 . Therefore, how we can find out the z transform of this that will be simply 1 . So will be we have found out $0.64 / 1 - 0.6 z$ into $1 - 0.6 z$ inverse plus this one is 1 . So if I carry out the algebra we will create this as denominator is $1 - 0.6 z$ into $1 - 0.6 z$ inverse.

And numerator will be $2 - 0.6$ into $z +$ inverse also RXYm in this case will be equal to Rx of m only. Therefore, S_{XZ} will be equal to S_X of z that is equal to we have already know this that is equal to 0.64 divided by $1 - 0.6 z$ into $1 - 0.6 z$ inverse. So this we have found out.

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$$H_{NC}(z) = \frac{S_{XY}(z)}{S_Y(z)} = \frac{\frac{0.64}{(1-0.6z)(1-0.6z^{-1})}}{\frac{2-0.6(z+1)}{(1-0.6z)(1-0.6z^{-1})}}$$

$$= \frac{0.64}{2-0.6(z+1)}$$

$$= \frac{0.455}{\left(1-\frac{1}{3}z\right)\left(1-\frac{1}{3}z^{-1}\right)}$$

if $V(N)=0$, then $S_Y(z) = S_X(z)$
 $\therefore H_{NC}(z) = \frac{S_{XY}(z)}{S_X(z)} = \frac{S_X(z)}{S_X(z)} = 1$

We can find out now the transfer function of the non causal Wiener filter that is HNCz that equal to S_{XZ} / S_{YZ} and this we have already found out $0.64 / 1 - 0.6 z$ into $1 - 0.6 z$ inverse / $2 - 0.6 z + z$ inverse / $1 - 0.6 z$ into $1 - 0.6 z$ inverse. So if we simplify we will get as $0.64 / 2 - 0.6$ into $z + z$ inverse. This we can further write in this standard form in the form like this suppose maybe some constant / $1 - c_1 z$ into $1 - c_1 z$ inverse.

So in this standard form we can write so z form it will come out we will see later on how to get this type of expression, but essentially this has to be factorized. So we will get this as $0.455 / 1 - 1 / 3$ of z into $1 - 1 / 3$ of z inverse. So this is the transfer function of the non-

causal Wiener filter H_{NCz} . Next part is what happened when $v_n = 0$. So if $v_n = 0$ then S_{Yz} will be simply equal to S_{xz} . Therefore, H_{NCz} will be that equal to S_{xYz} divided by S_{Yz} and this we have shown that this equal to S_{xz} divided by S_{xz} that equal to 1 because $S_{Yz} = S_{xz}$ therefore it will be 1 that means the signal will be passed as it is. Thank you.