

**Statistical Signal Processing**  
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**Lecture – 20**  
**Causal IIR Wiener Filter**

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**Let us recall**

The output  $\hat{X}(n)$  of a non-causal IIR filter is given by

$$\hat{X}(n) = \sum_{i=-\infty}^{\infty} h(i)Y(n-i)$$

❖ The filter coefficients  $h(j)$ s are obtained by minimizing the MSE

$$Ee^2(n) = E(X(n) - \sum_{i=-\infty}^{\infty} h(i)Y(n-i))^2$$

with respect to each  $h(j)$ .

❖ Applying the orthogonality principle, we get the WH equations

$$\sum_{i=-\infty}^{\infty} h(i) R_Y(j-i) = R_{XY}(j), \quad j = -\infty, \dots, \infty$$

❖ We solve the WH equations in the transform domain to get the transfer function

$$H(z) = \frac{S_{XY}(z)}{S_Y(z)}$$

Hello students, welcome this lecture on causal IIR Wiener filter, let us recall the output  $\hat{X}(n)$  of a non-causal IIR filter is given by this equation, we discussed non-causal IIR filter in the last class and the filter output is given by this equation. The filter coefficients  $h_j$ 's are obtained by minimizing the mean square error; mean square error is given by this expression,  $E$  of  $X(n)$  minus summation  $h_i$  into  $Y(n-i)$ ;  $i$  going from minus infinity to infinity whole square.

So, we have to minimize this expression with respect to  $h_j$ , now after applying the orthogonality principle we got the WH equation that is Wiener Hopf equations which are given by this relationship summation  $h_i$  into  $R_Y(j-i)$ ;  $i$  going from minus infinity to infinity is equal to  $R_{XY}(j)$  for  $j$  going from minus infinity to infinity, so this is an infinite set of equations and these equations can be solved in the transform domain by applying the Z transform, we get this relationship;  $H(z)$  is equal to  $S_{XY}(z)$  divided by  $S_Y(z)$ .

That is the cross power spectral density divided by power spectral density of the observed data, so this is the Wiener filter relationship in the case of non-causal IIR Wiener filter and this is quite simple.

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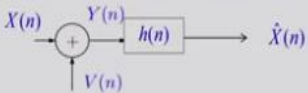
- ❖ Non-causal IIR Wiener filter is not realizable in real time.
- ❖ This lecture will explore the causal IIR Wiener filter which is realizable in real time.

The problem with non-causal IIR Wiener filter is that it is not realizable in real time, we cannot implement it in real time; this lecture will explore the causal IIR Wiener filter which is realizable in real time.

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**Causal IIR Wiener Filter**

- ❖ Consider the IIR filter to estimate the signal  $x(n)$  shown in the figure below.



- ❖ The estimator  $\hat{X}(n)$  is given by
$$\hat{X}(n) = \sum_{i=0}^{\infty} h(i)Y(n-i)$$
- ❖ The mean-square error of estimation is given by
$$Ee^2(n) = E(X(n) - \hat{X}(n))^2$$

$$= E(X(n) - \sum_{i=0}^{\infty} h(i)Y(n-i))^2$$

We have to minimize  $Ee^2(n)$  with respect to each  $h(j)$  to get the optimal estimator.

Let us consider this filtering problem; consider the IIR filter to estimate signal  $x_n$  as shown in figure below, this is the figure here,  $X_n + V_n$  that is our observed signal  $Y_n$  and we apply the IIR Wiener filter with filter coefficient  $h_n$  to get the estimated signal  $\hat{X}_n$ , so this is the IIR Wiener filter structure, there are infinite number of coefficients from  $h_0$  to  $h_{\infty}$ . The

estimator  $\hat{X}_n$  is given by  $\hat{X}_n$  is equal to summation  $h_i Y_{n-i}$ ;  $i$  going from 0 to infinity.

Because  $h_i$ 's are nonzero for  $i$  greater than equal to 0, the mean square error of estimation is given by this expression;  $E\{e^2_n}$  that is equal to  $E\{X_n - \hat{X}_n\}^2$  and if we substitute  $\hat{X}_n$  equals this, then we get  $E\{e^2_n}$  equal to  $E\{X_n - \sum_{i=0}^{\infty} h_i Y_{n-i}\}^2$ . So, this mean square error we have to minimize with respect to each  $h_j$ .

There are infinite number of  $h_j$ 's are there which respect to each  $h_j$ , we have to minimize this expression to get the optimal estimator.

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**Orthogonality principle and WH equations**

Our problem is

$$\underset{\text{over } h(j), j=0, \dots, \infty}{\text{Minimize}} \quad E\left(X(n) - \sum_{i=0}^{\infty} h(i)Y(n-i)\right)^2$$

❖ Applying the orthogonality principle, we get.

$$E\left(X(n) - \sum_{i=0}^{\infty} h(i)Y(n-i)\right)Y(n-j) = 0, \quad j = 0, \dots, \infty$$

$$\therefore \sum_{i=0}^{\infty} h(i) R_Y(j-i) = R_{XY}(j), \quad j = 0, \dots, \infty$$

which are the WH equations for the causal IIR Wiener filter.

❖ We have to find  $h(i)$ ,  $i = 0, 1, \dots, \infty$  by solving the above infinite set of WH equations.

Now, we can apply the orthogonality principle and get the Wiener Hopf equations, so applying the orthogonality principle we will get that is this part is error; error is orthogonal to each data point, so that way  $E\{X_n - \sum_{i=0}^{\infty} h_i Y_{n-i}\} Y_{n-j}$  must be equal to 0 for  $j$  is equal to 0 to infinity, so this is the orthogonality relationship which we have studied earlier.

Now, since we are considering WSS process, so  $Y_{n-j}$  into  $Y_{n-i}$  that will be  $R_Y$  of  $j-i$  similarly,  $X_n$  into  $Y_{n-j}$ , if we take the expectation we will get  $R_{XYj}$ , therefore we will get the Wiener Hopf equation that is given by summation  $h_i R_Y$  into  $j-i$ ;  $i$  going from 0 to infinity that is equal to  $R_{XYj}$ , for  $j$  equal to 0 to infinity. So, we have got the Wiener Hopf equations corresponding to causal IIR Wiener filter.

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**Difficulties in solving the WH equations**

- ❖ As the number of equations are infinite; they are better solved in the z-transform domain.
- ❖ We cannot directly apply the convolution theorem of z-transform, because  $\{h(i)\}$  is a one-sided sequence while  $\{R_y(i)\}$  is a two-sided sequence.
  - $h(i)$  is non-zero for  $i = 0, 1, \dots, \infty$
  - $R_y(i)$  is non-zero for  $i = -\infty, \dots, \infty$
- ❖ Here comes Wiener's contribution. The analysis is based on the spectral Factorization theorem for a regular random process:
$$S_y(z) = \sigma_v^2 H_c(z) H_c(z^{-1})$$

Now, we have to solve this infinite set of equations to find out  $h_i$  for  $i$  is equal to 0 to infinity. Now, what are the difficulties in solving the Wiener Hopf equations for causal IIR Wiener filters, as the number of equations are infinite, they are better solved in the z transform domain, we cannot directly apply the convolution theorem of z transform because  $h_i$  sequence that filter coefficient sequence is a one-sided sequence while that autocorrelation sequence is a two-sided sequence.

Thus we have  $h_i$  non zero for  $i$  is equal to 0 to infinity but  $R_y$  non zero for  $i$  is equal to minus infinity to infinity, so because of this we cannot apply the convolution theorem of z transform on the Wiener Hopf equations. Here comes Wiener's contribution; the analysis is based on the spectral factorization theorem for a regular random process that is  $S_y(z)$  is product of 2 vectors;  $\sigma_v^2$  into  $H_c(z)$  into  $H_c(z^{-1})$ .

And  $H_c(z)$  is a causal minimum phase transfer function and  $\sigma_v^2$  is the variance of the innovation process.

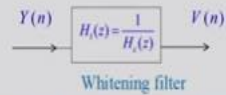
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### Solution steps

- ❖ Apply spectral factorization

$$S_y(z) = \sigma_v^2 H_r(z) H_r(z^{-1})$$

- ❖ Apply the whitening filter  $H_1(z) = \frac{1}{H_r(z)}$  to generate the innovation process  $V(n)$



- ❖ Estimate  $X(n)$  from  $V(n)$  using the causal IIR Wiener filter



So, by applying spectral factorization, we have  $S_y(z)$  is equal to  $\sigma_v^2$  into  $H_r(z)$  into  $H_r(z^{-1})$ , now we can apply the whitening filter because  $H_r(z)$  is a causal minimum phase filter therefore, we can invert it so, we can apply the whitening filter;  $H_1(z)$  is equal to  $1/H_r(z)$  to generate the innovation process  $V(n)$ , this  $V(n)$  is the innovation process, so this is the filtering  $X(n)$ , we pass  $Y(n)$  through  $H_1(z)$  is equal to  $1/H_r(z)$ , we will get  $V(n)$ .

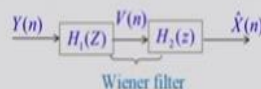
Now,  $V(n)$  is an uncorrelated sequence, it is easy to estimate  $X(n)$  from this  $V(n)$  sequence. So, we will estimate  $X(n)$  from  $V(n)$  by using the causal IIR Wiener filter principle, so  $V(n)$  you pass it through  $H_2(z)$ , we will get  $\hat{X}(n)$ .

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### Difficulties in solving the WH equations ...

- ❖ The filter  $H_2(z)$  is now used to estimate  $X(n)$  from  $V(n)$  using LMMSE criterion.

Then the causal Wiener filter will be  $H(z) = H_1(z)H_2(z)$  as shown below.



- ❖ Let  $h_2(n)$  be the Wiener filter coefficients to estimate  $X(n)$  from the innovation process  $V(n)$ . The estimator  $\hat{X}(n)$  is given by

$$\hat{X}(n) = \sum_{i=0}^n h_2(i) V(n-i)$$

- ❖ Our problem is to

$$\text{Minimize}_{h_2(i)} E(X(n) - \sum_{i=0}^n h_2(i) V(n-i))^2$$

The filter  $H_2(z)$  is now used to estimate  $X(n)$  from  $V(n)$  using the linear minimum mean square error criterion, then the causal Wiener filter will be  $H(z)$  is equal to  $H_1(z)$  into  $H_2(z)$ , where  $H_1(z)$  is

equal to 1 by  $H_z$  as we have shown earlier, this is the  $H_{1z}$ . So, we pass  $Y_n$  through  $H_{1z}$ , we get  $V_n$  and then using  $H_{2z}$ , we get  $\hat{X}_n$ , therefore our Wiener filter will be the cascaded filters  $H_{1z}$  and  $H_{2z}$ .

Or in other words, our  $H_z$  will be  $H_{1z}$  into  $H_{2z}$ , let  $h_{2n}$  be the Wiener filter coefficients to estimate  $X_n$  from the innovation process  $V_n$ , so here corresponding time domain parameters are  $h_{2n}$ . The estimator  $\hat{X}_n$  is now given by  $\hat{X}_n$  is equal to summation  $h_{2i} V$  of  $n - i$ ;  $i$  going from 0 to infinity and the corresponding minimization problem is minimize  $E$  of  $X_n$  minus summation  $h_{2i}$  into  $V$  of  $n - i$ ;  $i$  going from 0 to infinity whole square with respect to  $h_{2j}$ ,  $j$  going from 0 to infinity.

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**Wiener filter for the innovation process**

❖ Applying the orthogonality principle results in the WH equations

$$E(X(n) - \sum_{i=0}^{\infty} h_2(i)V(n-i))V(n-j) = 0, \quad j = 0, 1, \dots, \infty$$

$$\therefore \sum_{i=0}^{\infty} h_2(i)R_v(j-i) = R_{XV}(j), \quad j = 0, 1, \dots, \infty$$

❖ Note that

$$R_v(m) = \sigma_v^2 \delta(m)$$

$$\therefore \sum_{i=0}^{\infty} h_2(i) \sigma_v^2 \delta(j-i) = R_{XV}(j), \quad j = 0, 1, \dots, \infty$$

$$\Rightarrow h_2(j) \sigma_v^2 = R_{XV}(j), \quad j = 0, 1, \dots, \infty$$

$$\therefore h_2(j) = \frac{R_{XV}(j)}{\sigma_v^2}, \quad j = 0, 1, \dots, \infty$$

$$\Rightarrow H_2(z) = \frac{[S_{XV}(z)]_+}{\sigma_v^2}$$

where  $[S_{XV}(z)]_+$  is the positive part (part containing non-positive powers of  $z$ ) in the power series expansion of  $S_{XV}(z)$ .

Now, we will get the Wiener filter for the innovation process, applying the orthogonality principle results in the Wiener Hopf equations like this;  $E$  of  $X_n$  minus summation  $h_{2i}$  into  $V$  of  $n - i$ ;  $i$  going from 0 to infinity, this is the error and it is orthogonal to  $V$  of  $n - j$ ;  $j$  going from 0 to infinity, therefore  $E$  of  $X_n$  minus summation  $h_{2i}$  into  $V$  of  $n - i$ ;  $i$  going from 0 to infinity into  $V$  of  $n - j$  must be equal to 0 for  $j$  is equal to 0 to infinity.

Now, taking the expectation operation we will get that summation  $h_{2i}$  into  $R_v(j - i)$ ;  $i$  going from 0 to infinity that must be equal to  $R_{XV}(j)$ ,  $j$  going from 0 to infinity. So, this set of equations are the Wiener Hopf equations for the innovation process, note that  $R_{vm}$  is equal to  $\sigma_v^2 \delta(m)$  because innovation sequence is a white noise sequence, therefore its autocorrelation function is  $\sigma_v^2 \delta(m)$ .

It is  $\sigma_v^2$ , for,  $m$  is equal to 0 and 0 otherwise, therefore we will write this expression here therefore, we will get summation  $h_2(i) \sigma_v^2 \delta_{j-i}$ ;  $i$  going from 0 to infinity that must be equal to  $R_{XV}$  of  $j$ , for  $j$  equal to 0 to infinity. Now, this expression using the property of delta function, we get  $h_2(j)$  into  $\sigma_v^2$  that must be equal to  $R_{XV}$  of  $j$ , for  $j$  is equal to 0 to infinity, which gives  $h_2$  of  $j$  is equal to  $R_{XV}$  of  $j$  divided by  $\sigma_v^2$ .

And this is for  $j$  is equal to 0 to infinity, so we are able to find  $h_2(j)$  since our input process is a whitening process and taking the  $z$  transform of  $h_2(j)$ , we will get  $H_2(z)$  is equal to  $z$  transform of this divided by  $\sigma_v^2$ , so  $z$  transform of  $h_2(j)$  must be equal to  $z$  transform of  $R_{XV}$  of  $j$  divided by  $\sigma_v^2$  but here  $j$  is defined for 0 to infinity, therefore we have to consider only the positive part of the  $z$  transform that is  $H_2$  of  $z$  is equal to positive part of  $S_{XV}z$  divided by  $\sigma_v^2$ , where  $S_{XV}z$  plus is the positive part that is the part containing the non-positive powers of  $z$ .

That is  $z$  to the power 0,  $z$  to the power  $-1$ ,  $z$  to the power  $-2$  etc., in the power series expansion of  $S_{XV}z$ , therefore  $H_2z$  will be given by the positive part of  $S_{XV}z$  divided by  $\sigma_v^2$ .

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**Determination of  $H_2(z)$**

From

$$V(n) = \sum_{i=0}^{\infty} h_1(i) Y(n-i)$$

$$R_{XV}(j) = E X(n) V(n-j)$$

$$= \sum_{i=0}^{\infty} h_1(i) E X(n) Y(n-j-i)$$

$$= \sum_{i=0}^{\infty} h_1(i) R_{XV}(j+i)$$

$$S_{XV}(z) = H_1(z^{-1}) S_Y(z) = \frac{1}{H_1(z^{-1})} S_Y(z)$$

$$\therefore H_2(z) = \frac{1}{\sigma_v^2} \left[ \frac{S_{XV}(z)}{H_1(z^{-1})} \right]_+$$

Therefore, the causal IIR Wiener filter is given by

$$H(z) = H_1(z) H_2(z) = \frac{1}{\sigma_v^2 H_1(z)} \left[ \frac{S_{XV}(z)}{H_1(z^{-1})} \right]_+$$

So, how to determine  $H_2z$ ; we know that  $V_n$  is equal to summation  $i$  is equal to 0 to infinity  $h_1(i)$  into  $Y_{n-i}$ , so this is from the innovation representation of  $Y_n$ , so we get this relationship and taking the autocorrelation function, we will get  $R_{XV}$  of  $j$  is equal to  $E$  of  $X_n$  into  $V_{n-j}$ . So, therefore the  $R_{XV}$  of  $j$  will be equal to summation  $h_1(i)$  into  $E$  of  $X_n$  into  $Y_{n-j-i}$ ;  $i$  going

from 0 to infinity that will be equal to summation  $h_1 i$  into  $R_{xy} j + i$  because  $E$  of  $X_n$  into  $Y_n - j - i$  will give me  $R_{xy}$  of  $j + i$ .

And now if we take the  $z$  transform;  $S_{xv} z$  will be equal to  $H_1 z$  inverse into  $S_{xyz}$ , here  $j + i$  because of that this is  $H_1$  of  $z$  inverse into  $S_{xy}$  of  $z$  and I know  $H_1$  of  $z$  inverse is equal to 1 by  $H_e z$  inverse, therefore  $S_{xv}$  of  $z$  will be 1 by  $H_e z$  inverse into  $S_{xyz}$ , so we have  $H_2$  of  $z$  is equal to  $S_{xv}$  of  $z$  plus divided by  $\sigma_v^2$ , therefore we will substitute this expression, so we will get  $H_2 z$  is equal to 1 by  $\sigma_v^2$  into  $S_{xy}$  of  $z$  divided by  $H_e$  of  $z$  inverse plus; plus means the positive part.

Therefore, the causal IIR Wiener filter is given by  $H_z$  which is equal to  $H_1 z$  into  $H_2 z$  and  $H_1 z$  is given by 1 by  $H_e z$  and  $H_2 z$  is given by this, therefore the combined expression will be 1 by  $\sigma_v^2$  into  $H_e z$  into positive part of  $S_{xyz}$  divided by  $H_e z$  inverse, so this is the causal IIR Wiener filter expression.

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**Computing steps**

We have to

- Find the power spectrum  $S_y(z)$  using the available model or estimate it from the data
- Find the cross power spectrum  $S_{xy}(z)$  using the available model or estimate it from the data
- Factorize  $S_y(z)$  using the spectral factorization theorem

$$S_y(z) = \sigma_v^2 H_e(z) H_e(z^{-1})$$

- Compute the transfer function

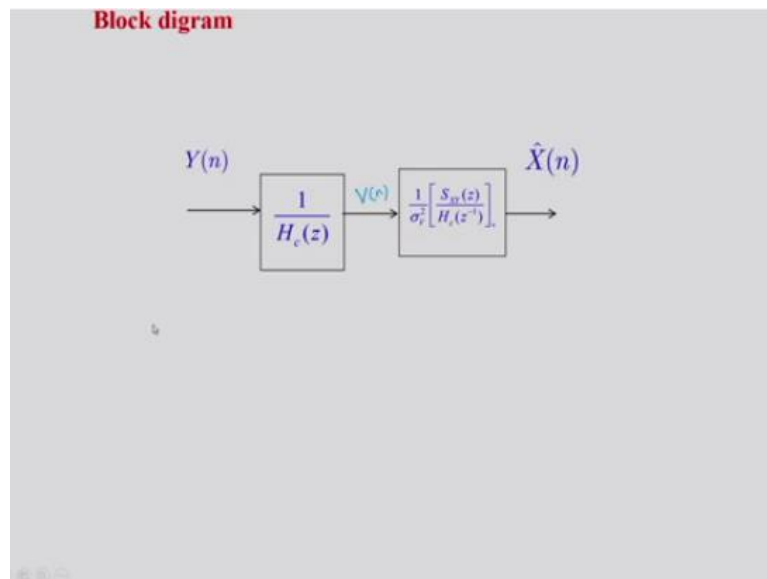
$$H(z) = \frac{1}{\sigma_v^2 H_e(z)} \left[ \frac{S_{xy}(z)}{H_e(z^{-1})} \right]_+$$

Let us see the computing steps; we have to find the power spectral density  $S_y z$  using the available model or estimate it from the data, we have to find the cross power spectrum  $S_{xy} z$  using the available model or estimated from the data, then we have to factorize  $S_y z$  using the spectral factorization theorem;  $S_y z$  is equal to  $\sigma_v^2$  into  $H_e z$  into  $H_e z$  inverse. If these things are available, then the transfer function of the IIR Wiener filter is given by  $H_z$  that is equal to 1 by  $\sigma_v^2$  into  $H_e z$  into the positive part of  $S_{xy} z$  divided by  $H_e z$  inverse.



So, He z inverse we get here, He z also we get here, sigma v square also we will get here and Sxy z we estimate or find from the model here.

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We can represent the procedure in a block diagram;  $Y_n$  is passed through this filter of transform function  $1/H_c(z)$  to get the innovation process  $V_n$ , which is now passed through this filter  $1/\sigma_v^2$  into the positive part of  $S_{xy}(z)$  divided by  $H_c(z)$  inverse and we will get the estimator  $\hat{X}_n$ . This is the principle of causal IIR Wiener filter.

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**Mean Square Estimation Error for causal IIR filter**

$$\begin{aligned}
 E(e^2(n)) &= E(e(n)(X(n) - \sum_{i=0}^{\infty} h(i)Y(n-i))) \\
 &= E(e(n)X(n)) \quad \because e(n) \text{ is orthogonal to the estimator} \\
 &= E(X(n) - \sum_{i=0}^{\infty} h(i)Y(n-i))X(n) \\
 &= R_X(0) - \sum_{i=0}^{\infty} h(i)R_{XY}(i) \\
 &= \frac{1}{2\pi} \int_{-\pi}^{\pi} S_X(\omega) d\omega - \frac{1}{2\pi} \int_{-\pi}^{\pi} H(\omega) S_{XY}^*(\omega) d\omega \\
 &= \frac{1}{2\pi} \int_{-\pi}^{\pi} (S_X(\omega) - H(\omega) S_{XY}^*(\omega)) d\omega \\
 &= \frac{1}{2\pi} \oint_C (S_X(z) - H(z) S_{XY}(z^{-1})) z^{-1} dz
 \end{aligned}$$

We have to find the mean square estimation error for the causal IIR Wiener filter and it is given by  $E(e^2(n))$  which can be written as  $E(e(n)(X(n) - \sum_{i=0}^{\infty} h(i)Y(n-i)))$ ;  $i$  going from 0 to infinity and using the orthogonality principle we will get this

expression is equal to  $E\{e_n^2}$ . Again, we are expanding  $e_n$ , so we will get  $E\{X_n^2 - 2\sum_{i=0}^{\infty} h_i X_{n-i} + \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} h_i h_j X_{n-i} X_{n-j}\}$ .

And after taking the expectation operation, we will get  $E\{X_n^2}$  that is  $R_x(0)$ , similarly this part will be  $\sum_{i=0}^{\infty} h_i R_{xy}(i)$ , so this is the mean square error of estimation and in terms of the transfer function we can get it in the frequency domain,  $R_x(0)$  is equal to  $\frac{1}{2\pi} \int_{-\pi}^{\pi} S_x(\omega) d\omega$  and  $\sum_{i=0}^{\infty} h_i R_{xy}(i)$  is equal to  $\frac{1}{2\pi} \int_{-\pi}^{\pi} H(\omega) S_{xy}(\omega) d\omega$ .

So, this is the expression for the mean square estimation error which we get by applying the inverse DTFT. Now, this same integral we can get in the  $z$  transform domain also where we have to perform the contour integral over a contour that includes the unit circle, so we will consider one contour in this  $z$  plane, this is the  $z$  plane and this is the contour  $c$  which includes the unit circle. Maybe somewhere a unit circle is here, this is unit circle.

So, if we perform this integral over this unit circle that is contour integral of  $S_x(z) - S_z$  into  $S_{xy}(z)$  inverse into  $z^{-1} dz$ , we will get the mean square error, so this way we can find out the mean square estimation error.

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**Example:** Consider the signal  $Y(n) = X(n) + V(n)$  with  $V(n)$  as a Gaussian white noise with variance 1 and  $X(n) = 0.8X(n-1) + W(n)$  where  $W(n)$  is a white noise with variance 0.68. The signal and noise are uncorrelated. Find the optimal causal Wiener filter to estimate  $X(n)$ .

**Solution:**

$$S_X(z) = \frac{0.68}{(1-0.8z^{-1})(1-0.8z)}$$

$$S_V(z) = 1$$

$$S_Y(z) = S_X(z) + S_V(z) = \frac{0.68}{(1-0.8z^{-1})(1-0.8z)} + 1$$

Let us consider one example; consider the signal  $Y_n$  is equal to  $X_n + V_n$  with  $V_n$  as a Gaussian white noise of variance 1 and  $X_n$  given by this model;  $X_n$  equal to  $0.8 X_{n-1} + W_n$ , where  $W_n$  is a white noise with variance 0.68, this signal  $X_n$  and the noise  $V_n$  are

uncorrelated. Find the optimal causal Wiener filter to estimate  $X_n$ ? So, first we will see what is the power spectral density of  $X_n$ .

So that way this model, this is here 1 model, you are passing WN that is the white noise through the filter  $1 - 0.8z^{-1}$  and we will get  $X_n$  that is the WSS output, so we can find out the power spectral density of  $X_n$  that is given by  $S_{Xz}$ , which is equal to 0.68 that is the variance of  $W_n$  divided by  $1 - 0.8z^{-1}$  that is  $8z$  into  $1 - 0.8z^{-1}$ , which is  $8z$  inverse, so that way we can find out the power spectral density of  $X_n$ .

$S_{Xz}$  is given by this and since  $V_n$  is a white noise of variance 1, its power spectral density is equal to 1, so we have to find out the power spectral density of  $Y_n$ , so this is my  $Y_n$  and I know that autocorrelation function of  $Y_n$  is equal to autocorrelation function of  $X_n$  + autocorrelation function of  $V_n$ , that we have analysed earlier, therefore we will get  $S_{Yz}$  that is power spectral density of  $Y$  is equal to  $S_{Xz} + S_{Vz}$ .

And this can be written like this 0.68 divided by  $1 - 0.8z^{-1}$  into  $1 - 0.8z^{-1}$  plus 1, so this is the power spectral density for  $Y_n$ .

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**Example ...**

Simplifying and factorizing, we get

$$S_Y(z) = \frac{0.68}{(1-0.8z^{-1})(1-0.8z)} + 1$$

$$= \frac{2(1-0.4z^{-1})(1-0.4z)}{(1-0.8z^{-1})(1-0.8z)}$$

$$\therefore H_c(z) = \frac{(1-0.4z^{-1})}{(1-0.8z^{-1})}$$

and

$$\sigma_v^2 = 2$$

Also

$$S_{Xz}(z) = S_X(z)$$

$$= \frac{0.68}{(1-0.8z^{-1})(1-0.8z)}$$

Simplifying and factorizing we will get this  $S_{Yz}$  can be written as this expression; 2 into  $1 - 0.4z^{-1}$  into  $1 - 0.4z$  divided by  $1 - 0.8z^{-1}$  into  $1 - 0.8z$ , so from this we will get  $\sigma_v^2$  is equal to 2 and causal part is  $1 - 0.4z^{-1}$  divided by  $1 - 0.8z^{-1}$ , this is the causal transfer function, therefore  $H_{cz}$  will be equal to  $1 - 0.4z^{-1}$  divided by  $1 - 0.8z^{-1}$ .

Also because it is signal and noise are uncorrelated, therefore we will get from the same model,  $S_{xy}(z)$  is equal to simply  $S_{xz}$  and which is given by 0.68 divided by  $1 - 0.8z^{-1}$  into  $1 - 0.4z^{-1}$ , so we have found out  $S_{xy}(z)$ , we have found out  $H_e(z)$  and we have the  $H_e(z)$  inverse also, this part is the  $H_e(z)$  inverse.

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Example ...

$$\begin{aligned} \therefore H(z) &= \frac{1}{\sigma_v^2 H_e(z)} \left[ \frac{S_{xy}(z)}{H_e(z^{-1})} \right] \\ &= \frac{1}{2(1-0.4z^{-1})} \left[ \frac{0.68}{\frac{(1-0.8z^{-1})(1-0.8z)}{(1-0.4z)}} \right] \\ &= \frac{1}{2(1-0.4z^{-1})} \left[ \frac{0.68}{(1-0.8z^{-1})(1-0.4z)} \right] \\ &= \frac{0.944}{(1-0.4z^{-1})} \\ h[n] &= 0.944(0.4)^n \quad n \geq 0 \end{aligned}$$

Now,  $H_z$  is equal to 1 by  $\sigma_v^2$  into  $H_e(z)$  into positive part of  $S_{xy}(z)$  divided by  $H_e(z)$  inverse, so we will substitute each term  $\sigma_v^2$  is equal to 2,  $H_e(z)$  is equal to this part and this part also,  $S_{xy}(z)$  is equal to this part and similarly,  $H_e(z)$  inverse is this part, so ultimately we will get an expression like this, we have to consider the positive part of this and we can get the positive part of this expression, this step transformed by partial expansion of this quantity 0.68 divided by  $1 - 0.8z^{-1}$  into  $1 - 0.4z^{-1}$ .

So, if we have the partial expansion and take the part containing  $1 - 0.8z^{-1}$  as the denominator, the part will be the positive part of the  $z$  transform because that part only will contain the non-positive powers of  $z$ , so therefore we will take the part and then simplify with this and ultimately, we will get  $H_z$  equal to 0.944 divided by  $1 - 0.4z^{-1}$ , so this is the transfer function of the IIR causal Wiener filter.

And correspondingly,  $h[n]$  also we can find out by taking the inverse transform  $h[n]$  will be 0.944 into 0.4 to the power  $n$ , for  $n$  greater than equal to 0, this will be defined for  $n$  equal to 0 to infinity, so that way we can find out the causal IIR Wiener filter.

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### Summary

- ❖ The estimator  $\hat{X}(n)$  using the causal IIR Wiener filter is given by

$$\hat{X}(n) = \sum_{i=0}^{\infty} h(i)Y(n-i)$$

- ❖ The mean-square error  $Ee^2(n) = E(X(n) - \hat{X}(n))^2$  is minimized with respect to each  $h(j)$  to get the optimal estimator.
- ❖ The WH equations are given by

$$\sum_{i=0}^{\infty} h(i) R_y(j-i) = R_{xy}(j), \quad j=0, \dots, \infty$$

which cannot be solved directly in the transform domain.

- ❖ We applied the spectral factorization theorem

$$S_y(z) = \sigma_v^2 H_v(z) H_v(z^{-1})$$

Let us summarize the lecture; the estimator  $\hat{X}(n)$  using the causal IIR Wiener filter is given by this relationship;  $\hat{X}(n)$  is equal to summation  $h_i$  into  $Y(n-i)$ ;  $i$  going from 0 to infinity. The mean square error  $E$  of  $e^2(n)$  that is equal to  $E$  of  $X(n) - \hat{X}(n)$  whole square is minimized with respect to each  $h_j$  to get the optimal estimator and the optimal estimator is given by the Wiener Hopf equations; summation  $h_i$  into  $R_y(j-i)$ ;  $i$  going from 0 to infinity is equal to  $R_{xy}(j)$ ; for  $j$  is equal to 0 to infinity.

And this set of Wiener Hopf equations cannot be solved directly in the transform domain, therefore we applied this spectral factorization theorem;  $S_y(z)$  is equal to  $\sigma_v^2$  into  $H_v(z)$  into  $H_v(z^{-1})$ .

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### Summary....

- ❖ Applied the whitening filter  $H_v(z) = \frac{1}{H_v(z)}$  to generate the innovation process

$$V(n).$$

- ❖  $X(n)$  now can be estimated from  $V(n)$  using the causal IIR Wiener filter

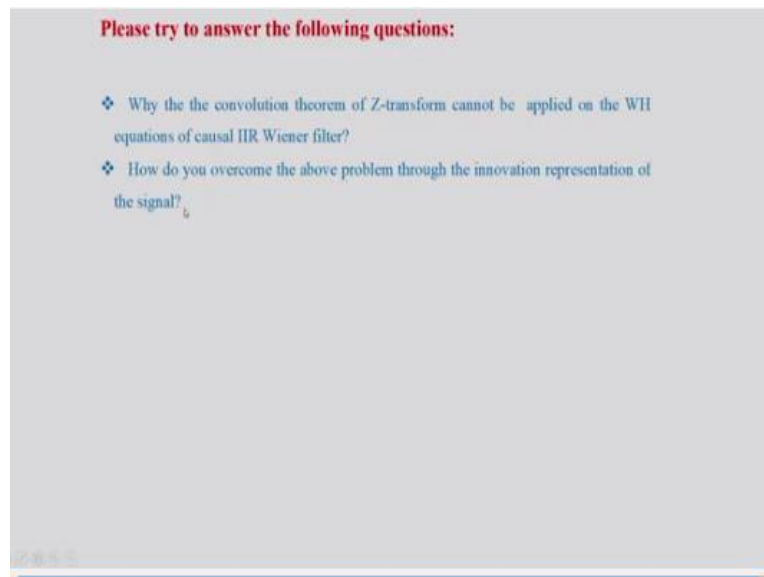
$$H_v(z) = \frac{1}{\sigma_v^2} \left[ \frac{S_{xy}(z)}{H_v(z^{-1})} \right]$$

- ❖ Finally, the causal IIR filter is given by

$$H(z) = \frac{1}{\sigma_v^2 H_v(z)} \left[ \frac{S_{xy}(z)}{H_v(z^{-1})} \right]$$

Then, we applied the whitening filter;  $H_1z$  is equal to 1 by  $H_ez$  to generate the innovation process  $V_n$ ,  $X_n$  now can be estimated from  $V_n$  using the causal IIR Wiener filter which was derived as  $H_2z$  equal to 1 by  $\sigma_v^2$  into positive part of  $S_{xyz}$  divided by  $H_ez$  inverse finally, the causal IIR Wiener filter is given by  $H_z$  that is equal to 1 by  $\sigma_v^2$  into  $H_ez$  into the positive part of  $S_{xyz}$  divided by  $H_ez$  inverse.

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So, we have to find  $S_{xy}$  of  $z$ ,  $H_ez$  inverse,  $H_ez$  and  $\sigma_v^2$ , then we can find out  $H_z$ , please try to answer the following questions; why the convolution theorem of  $Z$  transform cannot be applied on the Wiener Hopf equations of causal IIR Wiener filter, so we noted that we cannot apply the convolution theorem of  $Z$  transform directly only Wiener Hopf equations of causal IIR Wiener filter, why? How do you overcome the above problem through the innovation representation of the signal  $Y_n$ , so these 2 questions you try to answer, thank you.