

Statistical Signal Processing
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Lecture – 19
Noncausal IIR Wiener Filter

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Let us recall

- ❖ Output of an M-length FIR Wiener filter to input $Y(n)$ is given by
$$\hat{X}(n) = \sum_{i=0}^{M-1} h(i)Y(n-i)$$
- ❖ Applying the orthogonality principle, we get the WH equations
$$\sum_{i=0}^{M-1} h(i)R_y(j-i) = R_{xy}(j), \quad j=0,1,\dots,M-1$$
- ❖ M filter coefficients can be obtained by solving M equations.
- ❖ In matrix form, we have
$$\mathbf{R}_y \mathbf{h} = \mathbf{r}_{xy}$$
- ❖ $\mathbf{R}_y$ is a symmetric Toeplitz matrix.. This property is exploited to develop fast algorithms to compute $\mathbf{h}$.

Hello students, welcome to this lecture on non-causal Wiener IIR filter, let us recall the output of an M length FIR Wiener filter to input Y_n is given by this equation that is estimated signal $\hat{X}(n)$ is the summation $h(i)Y(n-i)$; i going from 0 to $M-1$, this is the M length Wiener filter output, applying the orthogonality principle we get the Wiener Hopf equations that is given by this relationship; summation $h(i)R_y(j-i)$; i going from 0 to $M-1$ equals R_{xy} of j .

These are the Wiener Hopf equations for j is equal to 0, 1, etc., up to $M-1$, there are M equations; therefore M filter coefficients can be obtained by solving these M equations. In matrix form, we write R_y matrix into $\mathbf{h}$ vector is equal to $\mathbf{r}_{xy}$ vector, this R_y is the correlation matrix, $\mathbf{h}$ is the filter coefficient vector and this is the cross correlation vector and we also noted that R_y is a symmetric Toeplitz matrix.

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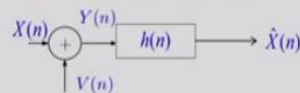
- ❖ Extending the procedure of FIR Wiener filtering to IIR filters is not easy because of the infinite number of WH equations.
- ❖ This lecture will explore how to deal with this problem in a relatively simple case of noncausal IIR filters.

This property is exploited to develop fast algorithms to compute $\hat{x}$, extending the procedure of FIR Wiener filtering to IIR filters is not easy because of the infinite number of Wiener Hopf equations, so we do not have any way to solve the infinite number of Wiener Hopf equations in the time domain. This lecture will explore how to deal with the problem in a relatively simple case of non-causal IIR filters.

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IIR Wiener filters

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



- ❖ We will consider two cases of IIR Wiener filters:

- Non-causal IIR Wiener filter or IIR Wiener smoother. $\hat{X}(n)$ is given by

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

$h(-\infty), \dots, h(\infty)$ is a two-sided sequence

- Causal Wiener filter. $\hat{X}(n)$ is given by

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

$h(0), \dots, h(\infty)$ is a one-sided sequence

- ❖ We will consider the non-causal Wiener filter first.

Consider the IIR filter to estimate signal x_n shown in the figure below, this is the filter suppose, this is $X_n + V_n$ that is Y_n and this is filtered by an IIR filter to get $\hat{X}_n$ and this h_n is an infinite duration sequence, we will consider 2 cases of IIR Wiener filters; first one is non-causal IIR Wiener filter or IIR Wiener smoother, it is also called a smoother. In this case, $\hat{X}_n$ is given by $\hat{X}_n$ is equal to summation h_i into Y_{n-i} ; i going from minus infinity to plus infinity.

The filter coefficients h minus infinity up to h infinity constitute a 2 sided sequence, here the filter coefficients forming 2 sided sequence, next is causal Wiener filter here, $\hat{X}(n)$ is given by $\hat{X}(n) = \sum_{i=0}^{\infty} h_i Y(n-i)$; i going from 0 to infinity, thus h_i are 0 for i less than 0, here h_0, h_1 up to h infinity a constitute a one-sided sequence, the filter coefficients form a one-sided sequence.

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Noncausal IIR Wiener filter

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

- ❖ Not realizable in real time
- ❖ The mean-square error of estimation is given by

$$Ee^2(n) = E(X(n) - \hat{X}(n))^2$$

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

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

We will consider the non-causal Wiener filter first and now, in this case as I have told $\hat{X}(n)$ is given by summation h_i into $Y(n-i)$; i going from minus infinity to plus infinity, this filter is not realizable in real time because the filtering involved future data here, there will be data corresponding to $Y(n+1), Y(n+2)$ etc., therefore this filter is not realizable in real time. Now, the mean square error of estimation is given by E of $e^2(n)$ that is E of $X(n)$ minus $\hat{X}(n)$ whole square.

And this I can expand E of $X(n)$ minus summation h_i into $Y(n-i)$; i going from minus infinity to infinity whole square, so this is the E of $e^2(n)$, we have to minimize E of $e^2(n)$ with respect to each h_j to get the optimal estimator, so we have to optimally estimate this h_j 's.

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Orthogonality principle and WH equations

Our problem is

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

❖ Applying the orthogonality principle, we get.

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

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

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

❖ These WH equations easily solved in frequency domain

Now, we will see how we can apply the orthogonality conditions to get the Wiener Hopf equations, our problem is to minimize E of X_n minus summation h_i into Y_{n-i} ; i going from minus infinity to infinity whole square over h_j , j going from minus infinity to infinity, this is our minimization problem, we have to minimize this mean square error with respect to all h_j . Applying the orthogonality principle, we get E of X_n minus summation h_i into Y_{n-i} ; i going from minus infinity to infinity into Y_{n-j} is equal to 0 for j is equal to minus infinity up to infinity.

Now, this equation can be rewritten as summation h_i into R_{Y_j-i} ; i going from minus infinity to infinity is equal to R_{XY_j} because E of X_n into Y_{n-j} will be equal to R_{XY_j} , similarly E of Y_{n-i} into Y_{n-j} will be R_Y of $j-i$, therefore we get this equation; summation h_i into R_{Y_j-i} ; i going from minus infinity to infinity that must be equal to R_{XY} of j , for j going from minus infinity to plus infinity.

So, therefore this is the equation which relates the autocorrelation of the data with the cross correlation now, this infinite set of equations are the Wiener Hopf equations for the non-causal IIR Wiener filter, this Wiener Hopf equations are easily solved in the frequency domain.

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Solution of WH equations.

❖ We have $h(j) * R_y(j) = R_{xy}(j)$, $j = -\infty, \dots, \infty$

❖ Applying the Z transform we get

$$H(z)S_y(z) = S_{xy}(z)$$

$$\therefore H(z) = \frac{S_{xy}(z)}{S_y(z)}$$

❖ Apply inverse Z-transform to find $h(n)$

❖ In frequency domain,

$$H(\omega) = \frac{S_{xy}(\omega)}{S_y(\omega)}$$

❖ Taking IDTFT,

$$h(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} H(\omega) e^{j\omega n} d\omega, \quad n \in \mathbb{Z}$$

Thus we have h_j convolve with R_{y_j} is equal to R_{xy_j} ; j going from minus infinity to plus infinity, so this is the relationship we have that is R_{xy_j} is the convolution of h_j and R_{y_j} , applying this Z transform we get, H_z , this is Z transform of h_j sequence into S_{yz} is equal to S_{xy_z} , this is the relationship in the Z transform domain, from which will get H_z is equal to xy_z divided by S_{yz} , so this is the power spectral density in terms of Z and this is the power spectral density in terms of Z.

Therefore, the transfer function or system function is the ratio of cross spectral density and power spectral density, therefore we have found out H_z and we can apply inverse Z transform to find h_n sequence. In the frequency domain we can write that is H_ω is equal to S_{xy_ω} divided by S_{y_ω} in terms of ω , we can write like this. Taking the IDTFT, inverse DTFT, we get h_n is equal to $\frac{1}{2\pi}$ integration minus π to π $H_\omega e^{j\omega n} d\omega$, where n belongs to $\mathbb{Z}$.

So, for all integers we can find out the filter coefficient, so we have found out the filter coefficients corresponding to non-causal IIR Wiener filter.

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Mean-square estimation error

❖ The mean square error of estimation is given by

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

Let us find out the mean square error of estimation; the mean square error of estimation is given by $E\{e^2(n)\}$ that is equal to $E\{e(n)X(n)\}$ because $e(n)$ is orthogonal to the estimator. We are writing like this, $X(n) - \sum_{i=-\infty}^{\infty} h(i)Y(n-i)$; i going from minus infinity to infinity and since $e(n)$ is orthogonal to this part, $e(n)$ is orthogonal to the estimator we can write $E\{e^2(n)\}$ is equal to $E\{e(n)X(n)\}$.

Again expanding $e(n)$, we can write MSE is equal to $E\{X(n) - \sum_{i=-\infty}^{\infty} h(i)Y(n-i)\}$; i going from minus infinity to infinity into $X(n)$, this is the mean square error. Now, $E\{X(n)X(n)\}$ will be equal to $R_X(0)$ similarly, $E\{Y(n-i)X(n)\}$ will be equal to $R_{XY}(i)$ so that way, $E\{e^2(n)\}$ MSE is equal to $R_X(0) - \sum_{i=-\infty}^{\infty} h(i)R_{XY}(i)$; i going from minus infinity to infinity.

And now, we can write this expression in terms of the DTFT, so that way $R_X(0)$ is $\frac{1}{2\pi} \int_{-\pi}^{\pi} S_X(\omega) d\omega$ minus $\frac{1}{2\pi} \int_{-\pi}^{\pi} H(\omega) S_{XY}^*(\omega) d\omega$ and we can simplify this expression because we can take this integral outside, so that way it will be equal to $\frac{1}{2\pi} \int_{-\pi}^{\pi} (S_X(\omega) - H(\omega) S_{XY}^*(\omega)) d\omega$.

So, this is the expression for mean square error and similarly, if we use a closed contour other than the unit circle, then we can write the $E\{e^2(n)\}$ in terms of Z transform like this, so this is the expression for mean square error.

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Noise filtering by noncausal IIR Wiener Filter: Expression for $H(\omega)$

- ❖ Consider the case of a carrier signal in presence of white Gaussian noise

$$Y(n) = X(n) + V(n)$$

where $V(n)$ is an additive zero-mean Gaussian white noise with variance σ_v^2 . Further, the signal and the noise are uncorrelated.

- ❖ We have

$$\begin{aligned} R_Y(m) &= E(X(n+m) + V(n+m))(X(n) + V(n)) \\ &= EX(n+m)X(n) + EX(n+m)V(n) + EV(n+m)X(n) + EV(n+m)V(n) \\ &= R_X(m) + R_V(m) \\ \therefore S_Y(\omega) &= S_X(\omega) + S_V(\omega) \end{aligned}$$

We will consider the case of noise filtering by non-causal IIR Wiener filters; consider the case of a carrier signal in presence of white Gaussian noise that is Y_n is equal to X_n ; X_n is a sinusoid + V_n , where V_n is an additive 0 mean Gaussian white noise with variance σ_v^2 , so this variance is σ_v^2 , further the signal and the noise are uncorrelated, this we assumed.

Now, we have $R_Y(m)$ by definition E of $X_{n+m} + V_{n+m}$ into $X_n + V_n$, now we can expand this term, we will get E of X_{n+m} into X_n , E of X_{n+m} into V_n , E of V_{n+m} into X_n + E of V_{n+m} into V_n , now signal and noise are uncorrelated, so this part will become 0, similarly this part will become 0, therefore we will have, this is R_X of m plus this quantity is R_V of m .

So, therefore R_Y is equal to R_X of m + R_V of m , taking the Fourier transform we will get S_Y of ω is equal to S_X of ω + S_V of ω , so this way we can compute the output power spectral density.

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Noise filtering by noncausal IIR Wiener Filter: Expression for $H(\omega)$

$$\begin{aligned}R_{XY}(m) &= EX(n+m)(X(n)+V(n)) \\&= EX(n+m)X(n) + EX(n+m)V(n) \\&= R_X(m) \\S_{XY}(\omega) &= S_X(\omega) \\\therefore H(\omega) &= \frac{S_{XY}(\omega)}{S_Y(\omega)} \\&= \frac{S_X(\omega)}{S_X(\omega) + S_V(\omega)}\end{aligned}$$

Similarly, $R_{XY}(m)$ that is the cross correlation between X of $n + m$ and Y_n and Y_n we will write as $X_n + V_n$, therefore R_{XY} of m will be equal to E of X of $n + m$ into $X_n + E$ of X of $n + m$ into V_n , now again this part is uncorrelated therefore, we will get simply R_{XY} of m is equal to R_X of m , so cross correlation between X of $n + m$ and X_n is equal to R_X of m , it is same as the autocorrelation of X_n sequence.

By taking the DTFT, we will get S_{XY} of ω will be simply S_X of ω , therefore (15:13) per function of the IIR non-causal Wiener filter that is $H(\omega)$ and it is given by $S_{XY}(\omega)$ divided by $S_Y(\omega)$ and $S_{XY}(\omega)$ is equal to $S_X(\omega)$ and $S_Y(\omega)$ is equal to $S_X(\omega) + S_V(\omega)$, therefore $H(\omega)$ will be equal to $S_X(\omega)$ divided by $S_X(\omega) + S_V(\omega)$.

So, this way we can determine the system function or transfer function of the non-causal IIR Wiener filter in terms of the power spectral densities of the signal and the observed data.

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Example

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

We have,

$W(n) \longrightarrow \boxed{\frac{1}{1-0.8z^{-1}}} \longrightarrow X(n)$

$$S_X(z) = \frac{0.68}{(1-0.8z^{-1})(1-0.8z)} \quad \text{and } S_V(z) = 1$$

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

$$\therefore S_Y(z) = S_X(z) + S_V(z)$$
$$= \frac{0.68}{(1-0.8z^{-1})(1-0.8z)} + 1$$
$$= \frac{2.32 - 0.8(z + z^{-1})}{(1-0.8z^{-1})(1-0.8z)} = \frac{2(1-0.4z^{-1})(1-0.4z)}{(1-0.8z^{-1})(1-0.8z)}$$

Let us consider one example; consider the signal Y_n equal to $X_n + V_n$, where V_n is a Gaussian white noise with variance 1 and X_n is equal to $0.8 X_{n-1} + W_n$, with W_n as zero mean white Gaussian noise with variance 0.68, this signal and noise are uncorrelated, find the optimal non-causal Wiener filter to estimate X_n ? So, we have observed signal model, signal plus noise, noise variance is given and signal model is given.

Therefore, we can find out the optimal non-causal Wiener filter to estimate X_n , now this signal model is like this, W_n is the input it passes through a filter of transfer function 1 by $1 - 0.8 z^{-1}$ and X_n is the output, this is the signal model because this is a white noise we can find out the power spectral density of the signal $S_X(z)$ is equal to variance of the white noise that is 0.68 divided by $1 - 0.8 z^{-1}$ into $1 - 0.8 z$.

So, we have use the relationship that is $S_X(z)$ is equal to σ_W^2 that is the variance of the white noise divided by $1 - 0.8 z^{-1}$ into $1 - 0.8 z$, 1 by this quantity is the causal transfer function and 1 by this quantity will be the corresponding non-causal transfer function and since V_n is a Gaussian white noise with variance 1, we can write $S_V(z)$ is equal to 1, so these are the power spectral density of the signal and the noise.

Now, $S_Y(z)$ is equal to $S_X(z) + S_V(z)$, we will write this expression and this expression we will get this result; $2.32 - 0.8 z + z^{-1}$ divided by $1 - 0.8 z^{-1}$ into $1 - 0.8 z$, now the numerator part also we can factorise, we can take 2 common and then we can factorize like this; 2 into $1 - 0.4 z^{-1}$ into $1 - 0.4 z$ divided by $1 - 0.8 z^{-1}$ into $1 - 0.8 z$, so this is the power spectral density of the output.

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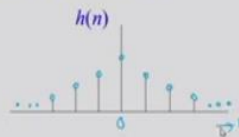
Example ...

$$\text{Also, } S_{xy}(z) = S_x(z) = \frac{0.68}{(1-0.8z^{-1})(1-0.8z)}$$

$$\therefore H(z) = \frac{S_{xy}(z)}{S_y(z)} = \frac{\frac{0.68}{(1-0.8z^{-1})(1-0.8z)}}{\frac{2(1-0.4z^{-1})(1-0.4z)}{(1-0.6z^{-1})(1-0.6z)}}$$

$$= \frac{0.34}{(1-0.4z^{-1})(1-0.4z)} \quad \text{One pole outside the unit circle}$$

$$= \frac{0.4048}{1-0.4z^{-1}} + \frac{0.4048}{1-0.4z}$$

$$\therefore h(n) = 0.4048(0.4)^n u(n) + 0.4048(0.4)^{-n} u(-n-1)$$


Now, S_{xyz} as we have shown it is equal to S_x of z and therefore it will be equal to 0.68 divided by $1 - 0.8z^{-1}$ into $1 - 0.8z$, therefore $H(z)$ that is the transfer function of the corresponding filter and that is given by S_{xyz} divided by S_yz and we will substitute the value of S_{xyz} and S_yz , we will get this expression, so 0.34 divided by $1 - 0.4z^{-1}$ into $1 - 0.4z$.

So, one pole will be inside the unit circle, other pole will be outside the unit circle and this we can expand like this; 0.4048 divided by $1 - 0.4z^{-1}$ + 0.4048 divided by $1 - 0.4z$ and this part will give the causal solution, this is given by this, 0.4048 into 0.4 to the power n $u(n)$; $u(n)$ is 1 for n greater than equal to 0 and this part will give an anti-causal sequence, 0.4048 into 0.4 to the power $-n$ because n is negative u of $-n - 1$.

So, if we plot $h(n)$ versus n , we will get a plot like this, so this $h(n)$ will be an infinite duration sequence extending from minus infinity to plus infinity.

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Qualitative interpretation of Wiener filtering

❖ We have

$$\begin{aligned} H(\omega) &= \frac{S_x(\omega)}{S_x(\omega) + S_v(\omega)} \\ &= \frac{\frac{S_x(\omega)}{S_v(\omega)}}{\frac{S_x(\omega)}{S_v(\omega)} + 1} \end{aligned}$$

❖ Suppose SNR is very high

$$H(\omega) \cong 1 \quad (\text{i.e. the signal will be passed un-attenuated}).$$

❖ When SNR is low

$$H(\omega) = \frac{S_x(\omega)}{S_v(\omega)}$$

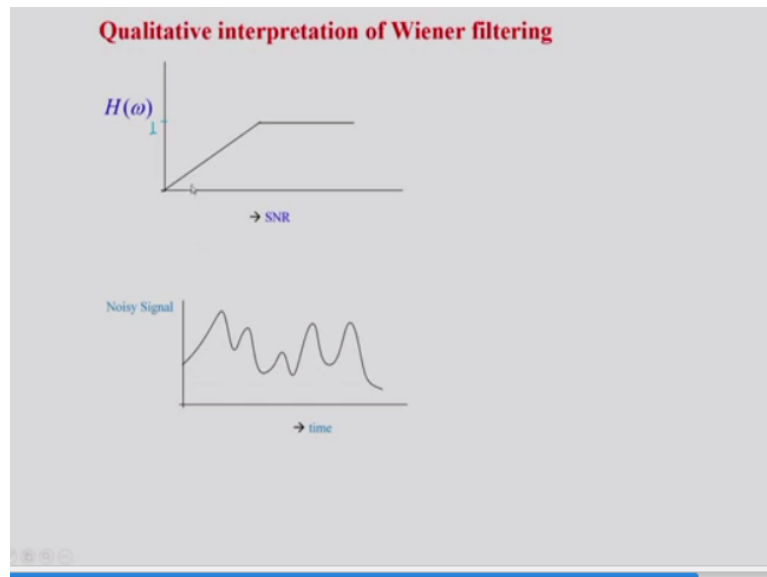
If the noise is high the corresponding signal component will be attenuated in proportion of the estimated SNR.

Let us give a qualitative interpretation of Wiener filter, we have established $H(\omega)$ is equal to $S_x(\omega)$ divided by $S_x(\omega) + S_v(\omega)$ and this we can write dividing both numerator and denominator by $S_v(\omega)$, we get $S_x(\omega)$ divided by $S_v(\omega)$, whole thing divided by $\frac{S_x(\omega)}{S_v(\omega)} + 1$. Now, this quantity is the signal to noise ratio, so this is SNR, here $\text{SNR} + 1$.

Suppose, SNR is very high in that case, this part will be dominant compared to 1 and therefore, this ratio will be almost equal to 1 and this means that signal will be passed un-attenuated that is when SNR is very high, signal quality is very high, now this is very less in that case, $H(\omega)$ is approximately equal to 1. When SNR is low this quantity will be approximately equal to 1.

So, therefore $H(\omega)$ will be $S_x(\omega)$ divided by $S_v(\omega)$ in other words, if the noise is high the correspondingly signal component will be attenuated in proportionate to the SNR because signal spectrum that is observed data spectrum will be multiplied by this quantity, this quantity is nothing but the signal to noise ratio therefore, if the noise is high the corresponding signal component will be attenuated in the proportion of the estimated SNR.

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We can plot $H(\omega)$ versus SNR. Suppose, when SNR is very low, in that case, $H(\omega)$ is equal to SNR, so that way this is a line of slope 1 and when SNR is high, $H(\omega)$ will be equal to 1, so that the signal will be passing unattenuated, so that way we can show that. Suppose, we are considering the case of sinusoid in the presence of noise in this part of the data, this signal quality is good therefore, $H(\omega)$ will be equal to 1.

And this part of data, the signal quality is low, SNR is low therefore, this transfer function will be equal to SNR, so that way we can qualitatively interpret the operation of non-causal IIR Wiener filter.

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Example: Image filtering by IIR Wiener filter

Original Image
Noisy

$S_x(\omega_1, \omega_2)$ = power spectrum of the corrupted image, estimated from the noisy image
 $S_f(\omega_1, \omega_2)$ = power spectrum of the noise, estimated from the noise model
 or from the constant intensity (like background) of the image

$$H(\omega_1, \omega_2) = \frac{S_x(\omega_1, \omega_2)}{S_x(\omega_1, \omega_2) + S_f(\omega_1, \omega_2)}$$

$$= \frac{S_x(\omega_1, \omega_2) - S_f(\omega_1, \omega_2)}{S_f(\omega_1, \omega_2)}$$

Let us consider one example that is the image filtering by IIR Wiener filter in this case, this is the original image and this is the noisy image. Suppose, this noisy image is obtained by adding

white Gaussian noise. Now, in this case because image is a 2 dimensional signal we have to apply the 2 dimensional Wiener filter and entire image is processed at a time, therefore we have the entire data suppose, if we consider a point here to the left of this point to the right of this point above this point or below this point all that are available.

Therefore, we can apply non-causal IIR Wiener filter, suppose $S_y(\omega_1, \omega_2)$ is the power spectrum of the corrupted image for this image which is generally estimated from the noisy image. Now, similarly we required the power spectrum of the noise so, $S_v(\omega_1, \omega_2)$ that is the power spectrum of the noise which can be estimated from the noise model or from the constant intensity portion of the image.

In the image some portion are there, where pixel intensity is uniform in that case from the variance of the noisy data we can find out the power spectrum of the noise and now the transfer function will be $H(\omega_1, \omega_2) = \frac{S_x(\omega_1, \omega_2)}{S_x(\omega_1, \omega_2) + S_v(\omega_1, \omega_2)}$ that is signal power spectrum divided by the power spectrum of the signal plus noise $S_x(\omega_1, \omega_2) + S_v(\omega_1, \omega_2)$.

But what is available for us is; $S_y(\omega_1, \omega_2)$ that is the power spectrum of the observed data, which is usually estimated, this part we can write as $S_y(\omega_1, \omega_2) = \frac{S_x(\omega_1, \omega_2)}{S_x(\omega_1, \omega_2) + S_v(\omega_1, \omega_2)}$ divided by the power spectrum of the observed noisy data, so that way we can determine the transfer function $H(\omega_1, \omega_2)$ by this relationship.

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Example: Image filtering by IIR Wiener filter...

$$\hat{X}(\omega_1, \omega_2) = H(\omega_1, \omega_2)Y(\omega_1, \omega_2)$$

Taking the inverse transform, we get the denoised image



Noisy Image



Wiener-Filtered Image

Once we have $H(\omega_1, \omega_2)$ we can determine the Fourier transform $\hat{X}(\omega_1, \omega_2)$ as $H(\omega_1, \omega_2)$ that is the transfer function multiplied by the Fourier transform of the output noisy image, $Y(\omega_1, \omega_2)$, taking the inverse DTFT or inverse transform we get the denoised image, this is example, so this is the noisy image. After this step, we get this Wiener filtered image.

So, this is an application of Wiener filter in 2 dimensions and here a non-causal Wiener filter is used because entire image data is thought out and then we process.

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Summary

- ❖ Non-causal estimator

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

- ❖ $h(j)$ 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,

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

Or equivalently

$$h(j) * R_Y(j) = R_{XY}(j)$$

Let us summarize the lecture that is non-causal IIR estimator is given by this $\hat{X}(n)$ is equal to summation $h_i Y(n-i)$; i going from minus infinity to plus infinity, h_j 's are obtained by minimizing this mean square error, this is the mean square error with respect to each of h_j , so we have to minimize E of $X(n) - \sum_{i=-\infty}^{\infty} h_i Y(n-i)$ whole square with respect to h_j .

Now, we applied the orthogonality condition and obtain the Wiener Hopf equation that is summation $h_i R_Y(j-i)$; i going from minus infinity to infinity that is equal to $R_{XY}(j)$, for any integer j or equivalently this $R_{XY}(j)$ is the convolution of h_j and $R_Y(j)$, this is the result.

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Summary...

❖ We have $h(j) * R_y(j) = R_{xy}(j)$, $j = -\infty, \dots, \infty$

❖ Applying the Z transform we get

$$H(z)S_y(z) = S_{xy}(z)$$

$$\therefore H(z) = \frac{S_{xy}(z)}{S_y(z)}$$

❖ Apply inverse Z-transform to find $h(n)$

❖ MSE

$$E(e^2(n)) = R_x(0) - \sum_{i=-\infty}^{\infty} h(i)R_{xy}(i)$$

$$\begin{aligned} &= \frac{1}{2\pi} \int_{-\pi}^{\pi} S_x(\omega) d\omega - \frac{1}{2\pi} \int_{-\pi}^{\pi} H(\omega) S_{xy}^*(\omega) d\omega \end{aligned}$$

And we can apply this Z transform now, Hz into Sxz that is equal to Sxyz, therefore Hz that is the system transfer function corresponding to IIR non-causal Wiener filter will be given by Sxyz divided by Syz and we can apply the inverse Z transform to find hn, so Hz is given therefore, we can find out hn and MSE that is mean square error is given by E of e square n that is equal to Rx of 0 minus this quantity summation hi into Rxy i; i going from minus infinity to infinity.

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Try to answer the following:

- ❖ Suppose $Y(n) = X(n)$. What will be the transfer function of the corresponding noncausal Wiener filter? What is the corresponding MSE?
- ❖ Can you implement a noncausal Wiener filter in real time? What additional constraint is required for the IIR filter to be realizable?
- ❖ We will discuss a realizable IIR Wiener filter in the next class.

This we can write in the frequency domain like this, try to answer the following questions; suppose Yn is equal to Xn, what will be the transfer function of the corresponding non-causal IIR Wiener filter, what is the corresponding MSE? This you can find out from the expressions for non-causal IIR Wiener filter and corresponding mean square error. Can you

implement a non-causal Wiener filter in real time, what additional constraint is required for the IIR filter to be realizable?

So, obviously answer to this question is no, you find out why it is no and then what additional constraint is required for IIR filter to be realizable, we will discuss a realizable IIR filter in the next lecture, thank you.