

Statistical Signal Processing
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Lecture-5
Linear Shift Invariant Systems with Random Inputs

Hello students, in the last lecture, we discussed the basics of random process we showed that is wide sense stationary random process WSS random process can be characterized in terms of its mean μ_x and the autocorrelation function R_x of x . We also showed the importance of power spectral density and how power spectral density is related with autocorrelation function. In this lecture, we discussed about linear invariant systems with random inputs. Why a linear model?

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Importance of the linear model

- ❖ In many applications, physical systems are modeled as linear time invariant (LTI) systems. Such a linear system is called a *linear filter* in signal processing.
- ❖ Finding linear filter that can optimally estimate a signal from the observed noisy data is an objective of SSP. The observed data and the signal are correlated. This correlation is exploited in optimal filtering.
- ❖ Many WSS signals are represented by linear models. The linear system theories plays an important roles in these models.

In this lecture, we will introduce the basic techniques to analyze the response of an LTI system to WSS random process.

In many applications, physical systems are modeled as linear time invariant systems, we will discuss what is LTI system such a linear system is called a linear filter in signal processing. So, filter and system they are used interchangeably in this course. Finding a linear filter that can optimally estimate a signal from the observed noisy data is an, objective of SSP the observed data and the signal are correlated that is one important observation that observed data and the signal are correlated.

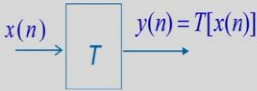
This correlation is exploited in optimal filtering so one application of linear filter is optimal filtering, which exploit the correlation between observed data and the unknown signal. Many WSS signals are represented by linear models. We will discuss about those linear models. The

linear system theories play an important role in these models. In this lecture will introduce the basic techniques to analyze the response of an LTI system to WSS random process as an input.

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LTI basics

- ❖ A system is modeled by a transformation T that maps an input signal $x(n)$ to an output signal $y(n)$. We can thus write,

$$y(n) = T[x(n)]$$


- ❖ **Linear system**

The system is called linear if superposition applies: **the weighted sum of inputs results in the weighted sum of the corresponding outputs.**

Thus for a linear system

$$T[a_1x_1(n) + a_2x_2(n)] = a_1T[x_1(n)] + a_2T[x_2(n)]$$

First, I will introduce the LTI basics. A system is modeled by transformation T that maps an input signal x_n to an output signal y_n . And we write $y_n = T x_n$. Thus, if x_n is the input the system is modeled by a transformation T and y_n is equal to $T x_n$ output. So, we know what is a system? System is basically modeled by transform. Now, linear system this system is called linear if superposition principle applies, what does it mean?

The weighted sum of inputs result in the weighted sum of the corresponding outputs. So, in terms of transformation this is the weighted sum $T a_1 x_1(n) + a_2 x_2(n)$ is same as $a_1 T x_1(n) + a_2 T x_2(n)$ and so, this is the weighted sum of the output a_1 times output due to $x_1(n) + a_2$ times output due to $x_2(n)$.

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❖ Time-invariant system

The system $y(n) = T[x(n)]$ is called time-invariant

if $T[x(n-n_0)] = y(n-n_0) \quad \forall n_0$

❖ Causal system

The system $y(n) = T[x(n)]$ is called causal if $y(n)$ depends on the present and past inputs only - $x(n), x(n-1), \dots$

We will be dealing with *linear time invariant (LTI)* causal systems

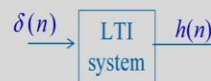
So, we saw what is a linear system. Now, time invariant system, this system $y_n = T$ of x_n is called time invariant if T of $x_n - n_0$ is same as $y_n - n_0$. So, if we have the delayed input, then the corresponding response will be also delayed. So, this is the time invariant system. Another important concept is causal system. The system $y_n = T$ of x_n is called causal if y_n depends on the present and the past inputs only. So, it does not depend on the present data so that way y_n is a function of $x_n, x_n - 1$ etcetera. We will be dealing with linear time invariant causal systems.

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Impulse response of a system

- ❖ An LTI system can be characterized by its impulse response $h(n) = T\delta(n)$ where $\delta(n)$ is the *unit impulse* function defined by

$$\delta(n) = \begin{cases} 1, & n = 0 \\ 0 & \text{otherwise} \end{cases}$$



- ❖ For a causal system, $h(n) = 0, n < 0$
- ❖ Depending on the duration for which $h(n) \neq 0$, *finite impulse response (FIR)* and *infinite impulse response (IIR)* systems.

This is very important we will discuss LTI causal systems impulse response of a system now a linear system is characterized by its impulse response. So, we will see what is an impulse response of a system? An LTI system can be characterized by its impulse response h_n it is

denoted by h_n is equal to transform of $\delta(n)$ so output due to impulse where $\delta(n)$ is the unit impulse in signal processing it is defined $\delta(n) = 1, n = 0$ otherwise, it is only at $n = 0$ there is an input.

So that way, suppose if this is my n axis, then suppose this is $n = 0, 1$ etc. So, at $n = 0$ the value of the signal is 1 and elsewhere it is 0. So, that way so this is the impulse signals. Now, impulse response is the response due to impulse so here is about the LTI system, your input is $\delta(n)$ corresponding output is called the impulse response and it is denoted by h_n now for a casual system $h_n = 0$ for n less than 0 because your $\delta(n)$ is nonzero.

Only at $n = 0$ therefore, for $n < 0$ h_n must be equal to 0 for a causal system. Depending on the duration for which h_n is nonzero finite impulses response FIR and in finite impulse response IIR systems are defined we will call suppose an FIR system for which the impulse response is a finite duration and IIR system for this impulse response is of infinite duration.

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System Output

❖ Any signal $x(n)$ can be represented in terms of $\delta(n)$ as follows

$$x(n) = \sum_{k=-\infty}^{\infty} x(k)\delta(n-k)$$

$$\therefore y(n) = Tx(n) = T \sum_{k=-\infty}^{\infty} x(k)\delta(n-k)$$

$$= \sum_{k=-\infty}^{\infty} x(k)T\delta(n-k)$$

$$= \sum_{k=-\infty}^{\infty} x(k)h(n,k)$$

where $h(n,k) = T\delta(n-k)$ is the response at time n due to the shifted impulse $\delta(n-k)$.

❖ If the system is time invariant,

$$h(n,k) = h(n-k) \text{ and}$$

$$y(n) = \sum_{k=-\infty}^{\infty} x(k)h(n-k) = x(n) * h(n) \quad (* \text{ denotes the convolution})$$

Now how to get the output of an LTI system any signal x_n can be represented in terms of $\delta(n)$ as follows that is x_n is summation x_k into $\delta(n - k)$, k going from minus infinity to plus infinity because we see that when we put $k = n$ here it will become $n - n = 0$ then it will be $\delta(0)$ is equal to 1 and for. So, when it is x_n that means this one will be $\delta(0)$ that is equal to 1 Therefore, it will be the right hand side will be x_n only for remaining values of n $\delta(n - k)$ will become 0.

So, that way x_n can be represented in terms of this infinite sum. Now, what will be the y_n will be transforming sum of x_n that is equal to the transformation of this sum. Now, we see that x_k the constant it is not a function of n . So, therefore, we can write T here so, this summation will be x_k into T times $\delta(n - k)$ and T of $\delta(n - k)$ that is the response due to delayed impulse is denoted by h of $n - k$ therefore y_n for a linear system will be summation x_k into $h(n - k)$, k going from minus infinity to plus infinity.

So, as I said this $h(n - k)$ is the response at time n due to this shifted impulse $\delta(n - k)$ h of $n - k$ this is the response at instant n due to the impulse at $n - k$. Now, suppose the system is time invariant the linear system is time invariant in that case, because the output due to the delayed impulse will be the will be just delayed impulse response. So, that way h of $n - k = h$ of $n - k$ for yet time invariant system.

So, in that case we can write y_n is equal to summation x_k into $h(n - k)$, k going from minus infinity to infinity and this is the convolution operation. Therefore, we can write x_n star h_n star is the convolution operation. So, what we have seen, if the system is time invariant system is linear and time invariant in that case, y_n output y_n , can we express the convolution of x_n input x_n and the impulse response h_n convolution of x_n and h_n .

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System Output ...

❖ If $y(n)$ is the output of LTI system with an impulse response $h(n)$ to a deterministic input $x(n)$, then

$$y(n) = \sum_{k=-\infty}^{\infty} x(k)h(n-k) = \sum_{k=-\infty}^{\infty} h(k)x(n-k) \quad (\text{convolution is commutative})$$

❖ In terms of filter terminology, $h(k)$ s are called *filter coefficients*.

❖ For a causal filter

$$h(k) = 0, \quad k < 0$$

❖ For a causal IIR filter

$$y(n) = \sum_{k=0}^{\infty} h(k)x(n-k)$$

❖ For a finite impulse response (FIR) filter $h(k) = 0, \quad k \geq M$

❖ Thus for a causal FIR filter

$$y(n) = \sum_{k=0}^{M-1} h(k)x(n-k)$$

Thus, if y_n is the output of an LTI system, which an impulse response h_n to deterministic input x_n y_n is the output of the LTI system to deterministic input x_n then y_n is equal to in the previous

expression so that it is summation x_k into h of $n - k$, k going from minus infinity to infinity. Now, noting that convolution is a commutative operation, we can write this as summation h_k into x of $n - k$, k going from minus infinity to infinity.

So, this is the output of an LTI system to a deterministic input x_n . Now, in terms of filter terminology, these h_k are called filter coefficients. For a causal filter if we assume that the filter is causal which is realizable $h_k = 0$ for k less than 0. So in that case we can write suppose for a causal IIR filter y_n will be equal to summation h_k into x of $n - k$, k going from 0 to infinity. So, if we put $h_k = 0$ for k less than 0.

We get this result upon a finite impulse response a FIR filter, $h_k = 0$ for k greater than equal to m for some constant m . So, therefore, what a causal FIR filter we can write y_n is equal to summation h_k into x of $n - k$, k going from 0 to $m - 1$. So, that way we have seen how to represent the output of a linear time invariant system in terms of the input and the impulse response of this system.

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Transform domain analysis

❖ We have, $y(n) = x(n) * h(n)$

❖ Taking the DTFT, we get

$$Y(\omega) = H(\omega) X(\omega)$$

$$\text{where } H(\omega) = \text{DTFT } h(n)$$

$$= \sum_{n=-\infty}^{\infty} h(n) e^{-j\omega n}$$

= the frequency response of the system

❖ In terms of z-transform,

$$Y(z) = H(z) X(z)$$

$$\text{where } H(z) = \sum_{n=-\infty}^{\infty} h(n) z^{-n}$$

= the transfer function of the system

Now, Let us see how we can represent the same result in the frequency domain we have $y_n = x_n * h_n$ variation is the impulse response which will be finite duration or infinite duration taking the DTFT in the, because it is a discrete time signal with take the discrete time Fourier transform taking the DTFT we get y omega that is Fourier transform of y_n discrete time Fourier transform of y_n is equal to it is convolution.

In time domain therefore, in frequency domain it will be multiplication that is $h(\omega)$ into $X(\omega)$, where $h(\omega)$ is the DTFT of $h(n)$ and we can write it as summation $h(n)$ into $e^{-j\omega n}$, n going from minus infinity to plus infinity. So this is the DTFT of $h(n)$ sequence. And this term in system theory, we call the frequency response of the system $h(\omega)$ is the frequency response of the system.

Therefore, discrete time Fourier transform of the output is equal to frequency response multiplied by the discrete time Fourier transform of the input. So if we write in terms of z transform, this will be $Y(z) = H(z)X(z)$. In fact, if we put that $h(z)$ is equal to $h(\omega)$ will get this expression. Where is that? It z transform of $h(n)$ and this is the expression, summation $h(n)$ into the z to the power $-n$ and going from minus infinity to plus infinity and is that. In system theory is called transfer function of the system for a discrete time system is that is the transfer function. Now, we have the background of the linear time invariant system.

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Response of an LTI system of impulse response $h(n)$ to WSS input $X(n)$

❖ The WSS process $X(n)$ is characterized by $\mu_X = EX(n)$ and autocorrelation function $R_X(m) = EX(n)X(n+m)$. PSD $S_X(\omega)$

Wide-sense stationarity of the output

We have $Y(n) = X(n) * h(n) = \sum_{k=-\infty}^{\infty} h(k)X(n-k)$

❖ Taking expectations of both sides,

$$\begin{aligned} EY(n) &= E \sum_{k=-\infty}^{\infty} h(k)X(n-k) \\ &= \sum_{k=-\infty}^{\infty} h(k)EX(n-k) \\ &= \sum_{k=-\infty}^{\infty} h(k)\mu_X \\ \therefore EY(n) &= \mu_X \sum_{k=-\infty}^{\infty} h(k) = \mu_X H(0) \end{aligned}$$

const

$$H(\omega) = \sum_{n=-\infty}^{\infty} h(n)e^{-j\omega n}$$

$$H(0) = \sum_{n=-\infty}^{\infty} h(n)e^{-j0 \cdot n} = \sum_{n=-\infty}^{\infty} h(n)$$

Let us discuss the response of an LTI system of impulse response $h(n)$ to a WSS input $x(n)$. So, impulse response is $h(n)$ and input $X(n)$ is WSS that we assume now you know that the WSS process $X(n)$ is characterized by mean μ_X that is E of $X(n)$ and autocorrelation function R_X of m that is E of $X(n)X(n+m)$. And also we can collect as because autocorrelation function had the Fourier transform power spectral density. Therefore, we can also characterize the WSS process in terms of power spectral density $S_X(\omega)$ PSD, $S_X(\omega)$.

So, these are the quantities which characterize a WSS random process mean μ_x autocorrelation R_X of m and PSD S_x of ω . Now input is a WSS signal whatever the output so will prove the wide sense stationarity of the output we have $Y_n = X_n$ convolved with h_n that is equal to summation $h_k X_{n-k}$, k going from minus infinity to plus infinity. Let us take expectations of both sides, then E of Y_n will be E of this sum.

This is the expectation of summation and these we can write as summation k going from infinity to plus infinity h_k into E of X_{n-k} because h_k is a constant random variable. So, therefore, expectation operation will come here and this we can write E of Y_n will be equal to summation h_k into μ_x because this quantity is constant at every time point therefore, we can write it as μ_x that is the h_{Xn} is a WSS process this quantity will be μ_x .

So, what we conclude E of $Y_n = \mu_x$, μ_x we are taking out into summation of h_k , k going from minus infinity to plus infinity. This quantity is the frequency response at 0 frequency or 0 frequency gain how because it can write suppose we have $h(\omega)$ is equal to summation h_n into $e^{j\omega n}$, n going from minus infinity to plus infinity. Now will put ω is equal to 0 is 0 will be equal to summation $h_n e^{j0}$, $j0$ into n .

And that will be 1 and going from minus infinity to plus infinity. That is equal to summation h_n and going from minus infinity to plus infinity, so that way E of Y_n is equal to μ_x into $h(0)$ What does it mean? That E of Y_n is a constant now, this is a constant, this quantity is a constant so, this is one of the requirements for WSS process that process should have constant mean and we have seen that Y_n has constant mean.

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Wide-sense stationarity of the output

$$\begin{aligned}
 EX(n)Y(n+m) &= E \sum_{k=-\infty}^{\infty} h(k)X(n+m-k) \\
 &= \sum_{k=-\infty}^{\infty} h(k)E X(n)X(n+m-k) \\
 &= \sum_{k=-\infty}^{\infty} h(k)R_X(m-k) \text{ (function of } m \text{ only)} \\
 \therefore R_{XY}(m) &= R_X(m) * h(m)
 \end{aligned}$$

Similarly,

$$\begin{aligned}
 EY(n)Y(n+m) &= h(-m) * R_{YY}(m) \\
 \therefore R_Y(m) &= h(-m) * R_{YY}(m) = h(-m) * h(m) * R_X(m)
 \end{aligned}$$

Therefore, if $Y(n)$ is the response of an LTI system of impulse response $h(n)$ to WSS input $X(n)$, then

- (a) $X(n)$ and $Y(n)$ are jointly WSS and
- (b) $\mu_Y = \mu_X H(0)$ and $R_Y(m) = h(m) * h(-m) * R_X(m)$

Will continue about to wide sense stationarity of the output. Let us see what happened to the cross correlation function, E of X_n into Y_{n+m} that is equal to E of X_n into and Y of $n+m$ that is summation or convolution of X_n and Y_{n+m} so that we can write a summation h_k into X of $n+m-k$, k going from minus infinity to plus infinity. Now, we can take E inside because these are a constant quantity, so E of X_n into X of $n+m-k$.

Now, using the WSS concept, this quantity will be a function of the lag $n+m-k-n$ that is the lag that is equal to $m-k$ therefore, this cross correlation function is equal to summation h_k into R_x of $m-k$, k going from minus infinity to plus infinity. So, we see that this is a function of lag only, it does not depend on n and therefore, we can write $R_{xy}(m)$ that is the cross correlation function at lag m is equal to R_x of m , R_x of m convolved with h of m .

Similarly, we can write E of Y_n into $Y_{n+m} = h$ of $-m$ convolved with R_{yy} of m . So, here again if we substitute Y_n is equal to summation $h_k X$ of $n-k$, k going from minus infinity to plus infinity, then we will get this result. So, here again we will see that it is a function of lag m only, we can write $R_y(m)$ that is output autocorrelation function is equal to h of $-m$ convolved with $R_{xy}(m)$ and from this result will write this equal to h of $-m$ convolved with h of m convolved with R_x of m so, this is the output autocorrelation function.

And what we conclude? We conclude that if Y_n is the response of an LTI system of impulse response h_n , to WSS input X_n then X_n and Y_n are jointly WSS. Because, output y_n is a WSS process X_n is the WSS process and their cross correlation depends only on lag. Therefore, X_n and Y_n are jointly WSS and second conclusion is that μ_y is equal to μ_x into H_0 where H_0 is the 0 frequency gain or this gain and $R_y(m)$ is the convolution of $h(m-m)$ and $R_x(m)$ so these are the results we established. This is the characterization in time domain. So, these are characterization in the time domain in the frequency domain we will see what happened.

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Power Spectrum of the output

❖ We have $R_y(m) = h(-m) * h(m) * R_x(m)$

❖ Taking DTFT,

$$S_y(\omega) = H^*(\omega)H(\omega)S_x(\omega) = |H(\omega)|^2 S_x(\omega)$$

Thus, the spectral properties of a WSS signal can be modified by passing it through a linear filter.

❖ In terms of z-transform,

$$S_y(z) = H(z^{-1})H(z)S_x(z)$$

Power spectrum of the output, we have $R_y(m) = h(-m) * h(m) * R_x(m)$. Now again, we will take the DTFT so, DTFT of $R_y(m)$ is $S_y(\omega)$. So, that will be equal to now $h(-m)$, if we take the DTFT that will be $H^*(\omega)$ complex conjugates of $H(\omega)$ into $H(\omega)$ into $S_x(\omega)$ PSD of x_n so, because convolution in time domain will be multiplication in the frequency domain we get this result.

Now $H^*(\omega)H(\omega)$ that is mod of $H(\omega)$ Square therefore, $S_y(\omega)$ will be equal to mod of $H(\omega)$ square into $S_x(\omega)$. So, this is the relationship between PSD of the output and PSD of the input. Thus this spectral properties of a WSS signal can be modified this is modified because this function is multiplying $S_x(\omega)$. So, $S_x(\omega)$ will be now modified can be modified by passing it through a linear filter.

So, this power spectrum we can also express in terms of z transform. So, that $S_y(z)$ will be equal to H and inverse that transform of this will be $H(z)$ inverse into $H(z)$ into $S_x(z)$ this is $S_y(z)$ will be generalized PSD of the output process $S_x(z)$ their generalized PSD of the input process. Will consider one example,

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Example

A discrete-time WSS process $X(n)$ with $\mu_X = 0$ and $R_X(m) = \begin{cases} 1, & m=0 \\ 0 & \text{otherwise} \end{cases}$ is input to an FIR filter with filter coefficients $h(n) = \begin{cases} 1, & n=0,1 \\ 0 & \text{otherwise} \end{cases}$. Find the mean, the PSD and the autocorrelation function of the output process.

Solution:
The frequency response of the system is given by

$$H(\omega) = \sum_{n=-\infty}^{\infty} h(n)e^{-j\omega n} = 1 + e^{-j\omega}$$

The output mean is given by

$$\mu_Y = \mu_X \times H(0) = 0$$

The PSD of the input process $X(n)$ is given by with power spectral density

$$S_X(\omega) = \sum_{m=-\infty}^{\infty} R_X(m)e^{-j\omega m} = R_X(0)e^{-j\omega \cdot 0} = 1, \quad |\omega| \leq \pi$$

A discrete time WSS process X_n with $\mu_x = 0$ and the autocorrelation function R_{xm} . Which is equal to 1 at a $\mu = 0$ and 0 otherwise, input to FIR filter with filter coefficient h_n is equal to 1 for $n = 0$ and $n = 1$ and 0 otherwise it is the 2 type filter, only 2 values $h_0 = 1$ and h_1 is also equal to 1. Find the mean the PSD and the autocorrelation function of the output process will find the solution here.

The frequency response of the system because this is the impulse response, we have to take the DTFT. So frequency response of the filter is given by summation $h_n e^{-j\omega n}$ and n going from minus infinity to plus infinity but here for all other value of n $h_n = 0$ only at $n = 0$ and 1 will get $h_n = 1$ therefore will have this is h_0 that is 1 into e to the power $j\omega \cdot 0$ that will be equal to $1 + h_1$ that is 1 into e to the power $-j\omega \cdot 1$ that is equal to $-j\omega$. So that way $h(\omega)$ will be $1 + e^{-j\omega}$.

Once we know $h(\omega)$ we can find out the output means that is equal to μ_y into μ_x is H of 0 and we know that $\mu_x = 0$ therefore this will be equal to 0. So, therefore output of this filter is 0 mean. Now, we have to find out the output power spectral density before that we have to find

out what is input power spectral density, that is $S_x(\omega)$ is equal to summation $R_x(m)$ into $e^{-j\omega m}$, m going from minus infinity to infinity.

So, here only one value of $R_x(m)$ is non 0 that is at time is equal to 0 it is 1 otherwise it is 0 therefore, it will be equal to $R_x(0)$ into $e^{-j\omega \cdot 0}$ that is equal to 1 for ω anyway power spectral density is uniquely defined because it is a discrete time fourier transform it is uniquely defined in a period from $-\pi$ to π . So, that way $S_x(\omega) = 1$ for $-\pi < \omega < \pi$.

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Example contd...

The output PSD

$$\begin{aligned} S_y(\omega) &= |H(\omega)|^2 S_x(\omega) \\ &= 1 \times |1 + e^{-j\omega}|^2 \\ &= 2 + 2 \cos \omega \quad |\omega| \leq \pi \quad S_y(\omega) = \sum_{m=-\infty}^{\infty} R_y(m) e^{-j\omega m} \\ &= 2 + e^{j\omega} + e^{-j\omega} \end{aligned}$$

By inspection,

$$R_y(0) = 2, R_y(-1) = R_y(1) = 1, R_y(m) = 0, |m| > 1$$

Now, we can find out the output PSD. So, the output PSD is given by $S_y(\omega)$, that is equal to mod of $x(\omega)$ square into $S_x(\omega)$ and we know $S_x(\omega)$ is equal to 1 therefore, $1 \times |1 + e^{-j\omega}|^2$ and this we can write as if we expand it, we will get it as $2 + 2 \cos \omega$ or mod of ω is less than equal to π , because DTFT is uniquely defined in a period from $-\pi$ to π .

And this $\cos \omega$ again we write in terms of $e^{j\omega} + e^{-j\omega}$. So, that we can now compare with this expression $S_y(\omega)$ is equal to summation $R_y(m)$ into $e^{-j\omega m}$, m going from minus infinity to plus infinity. Here we see that only 2 times are there corresponding to ω is equal to 0, ω is equal to $-\pi$ and ω is equal to $+\pi$.

So, therefore, the corresponding coefficient will be the autocorrelation function, therefore, by inspection R_y of 0 = 2 R_y of -1 will be equal to R_y of 1 will be equal to 1 and for rest of the values of m R_y m will be equal to 0.

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Summary

❖ For an LTI system with impulse response $h(n)$ and input $x(n)$, the output is given by

$$y(n) = \sum_{k=-\infty}^{\infty} h(k)x(n-k) = x(n) * h(n)$$

❖ If the system is causal, then

$$y(n) = \sum_{k=0}^{\infty} h(k)x(n-k)$$

❖ In the transform domain.

$$Y(\omega) = H(\omega) X(\omega).$$

$$H(\omega) = \text{DTFT}(h(n)) = \text{Frequency response of the system}$$

$$Y(z) = H(z) X(z), \text{ Transfer function } H(z) = Z\text{-transform of } h(n)$$

Let us summaries what we have learned today for an LTI system with impulse response h_n and input x_n the output is given by this convolution relation x_n convolve with h_n and if we expand that will be equal to k summation h_k into x of $n - k$, k going from minus infinity to plus infinity this is the output of a linear time invariant system due to an input action. Now, if the system is causal, in that case, h_k is equals 0 for k less than 0 therefore, a y_n will be equal to summation h_k x of $n - k$, k going from 0 to infinity.

In the transform domain we have Y omega is equal to H omega into X omega. This is by taking the DTFT we get this relationship and this H omega DTFT of h_n is known as the frequency response of the system. And similarly we can write z transform domain $Y z = H z$ into $X z$ and where transfer function $H z$ is equal to z transform of h_n .

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Summary Contd...

- ❖ A WSS process $X(n)$ is characterized by its mean μ_x and autocorrelation function $R_x(m)$ PSD $S_X(\omega)$
- ❖ For an LTI system with impulse response $h(n)$ and WSS input $X(n)$,
 - $X(n)$ and output $Y(n)$ are jointly WSS
 - $\mu_y = \mu_x H(0)$
 - $R_y(m) = h(m) * h(-m) * R_x(m)$
 - $S_y(\omega) = |H(\omega)|^2 S_x(\omega)$
 - $S_y(z) = H(z)H(z^{-1})S_x(z)$

THANK YOU

Coming to the random process a WSS process X_n is characterized by its mean μ_x and the autocorrelation function R_x of m . So, WSS process X_n is represented by its mean μ_x and the autocorrelation function R_x of m also deeper PSD S_x of ω for an LTI system with impulse response h_n and WSS input X_n input X_n and output Y_n are jointly WSS that we established. Then μ_y that is mean of the output process is equal to mean of the input process multiplied by H_0 where H_0 is the this gain of this system or 0 frequency gain of the system.

The autocorrelation function of the output process R_y of m is given by h_m convolved with h of $-m$ convolved with R_x of m it is the convolution of h_m $h(-m)$ and R_x of m and in the frequency domain we get. S_y of ω is equal to mod of H of ω square into S_x of ω also in terms of z transform S_y of z that is generalized PSD is equal to H_z , H_z inverse into S_x of z . Thank you.