EE20N: Structure and Interpretation of Systems and Signals

Fall 2013

Lecture 14: October 17

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## 14.1 Announcements

• Guest lecture next Tuesday - Professor Miki Lustig (MRI)

• Reading: Chapter 10 of Lee and Varaiya

• Lecture notes posted have extra material.

## 14.2 Agenda

• DTFT - Discrete-time Fourier transform

• DFT - Discrete Fourier transform

# 14.3 Recap of DTFT

The DTFT allows us to find the spectrum of non-periodic signals. It provides us the Fourier representation of aperiodic signals.

$$x(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X_d(\omega) e^{i\omega n} d\omega$$

Recall that when x(n) is periodic with period p:

$$x_p(n) = \frac{1}{p} \sum_{k=0}^{p-1} X(k)e^{iw_0kn}, w_0 = \frac{2\pi}{p}$$

Periodic (Fourier Series): x(n) is a discrete sum of weighted complex exponentials.

$$\{e^{i\omega_0 kn}\}_{k=0}^{p-1}$$

Aperiodic (Discrete-time Fourier transform):  $\mathbf{x}(\mathbf{n})$  is an "infinite sum" (i.e. integral) of complex exponentials  $e^{i\omega n}, \forall \omega \in [-\pi, \pi]$  with weights given by  $X_d(\omega)$  for frequency  $\omega$ .

# 14.4 Relate the DTFT to Frequency Response

Why is  $Y_d(\omega) = X_d(\omega)H(e^{i\omega})$ ? The synthesis equation of the DTFT shows that:

$$x(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X_d(\omega) e^{i\omega n} d\omega$$

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Figure 14.1: LTI system represented in time and frequency

$$y(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} Y_d(\omega) e^{i\omega n} d\omega$$

We know that in LTI systems for an input  $x(n) = e^{i\omega_0 n}$  the output is  $y(n) = H(e^{i\omega_0})e^{i\omega_0 n}$ . That is, for any complex exponential input, the output is simply the input signal scaled by the frequency response. We can think of  $X_d(\omega)$  as the set of all input exponentials in the input signal, each of which is scaled appropriately by  $H(e^{i\omega})$  By the LTI property:

$$y(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X_d(\omega) H(e^{i\omega}) e^{i\omega n} d\omega$$
$$Y_d(\omega) = X_d(\omega) H(e^{i\omega})$$

#### Theorem 14.1.

 $DTFT[OUTPUT] = DTFT[INPUT] \times [Frequency\ response\ of\ LTI\ system]$ 

The DTFT of the output of a system is equal to the DTFT of the input signal multiplied by the frequency response of the system.

Recall, the DTFT $[\delta(n)] = 1, \forall \omega$ . Apply our new theorem to this example:

$$\chi(n) = S(n) \rightarrow h(n) \rightarrow y(n) = h(n)$$

$$\downarrow \downarrow \qquad \qquad \downarrow \downarrow \downarrow$$

$$\chi_{d}(\omega) = 1 \qquad \qquad \chi_{d}(\omega) = H_{d}(\omega)$$

Figure 14.2: LTI system with  $x(n) = \delta(n)$ 

$$X_d(\omega) \times H(e^{i\omega}) = Y_d(\omega) = H_d(\omega) = H(e^{i\omega})$$
Freq. resp. of sys.

**Theorem 14.2.**  $H(e^{i\omega})$ , the frequency response of an LTI system is the DTFT of the impulse response h(n) of the system.

$$h(n) \stackrel{DTFT}{\longleftrightarrow} H(e^{i\omega})$$

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Question: How to go from x(n) to  $X_d(\omega)$ ?

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

$$x(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X_d(\omega) e^{i\omega n} d\omega$$

Given the linearity of the integral operator in the DTFT:

$$x_1(n) \longleftrightarrow X_{1,d}(\omega)$$

$$x_2(n) \longleftrightarrow X_{2,d}(\omega)$$

$$x_1(n) + x_2(n) \longleftrightarrow X_{1,d}(\omega) + X_{2,d}(\omega)$$

$$\alpha_1 x_1(n) + \alpha_2 x_2(n) \longleftrightarrow \alpha_1 X_{1,d}(\omega) + \alpha_2 X_{2,d}(\omega)$$

The above follows because the synthesis equation is linear. x(n) is just a weighted sum of shifted impulses, therefore we need to find the DTFT[ $\delta(n-k)$ ].

$$x(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X_d(\omega) e^{i\omega n} d\omega$$

What is x(n-10)?

$$x(n-10) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X_d(\omega) e^{i\omega(n-10)} d\omega = \frac{1}{2\pi} \int_{-\pi}^{\pi} X_d(\omega) e^{-i\omega 10} e^{i\omega n} d\omega$$

What is DTFT[x(n-10)]?

$$DTFT[x(n-10)] = X_d(\omega)e^{-i\omega 10}$$

Let's look at these Fourier transform pairs. The time domain representation will be shown in red, and the frequency domain representation will be shown in blue.

$$\frac{\mathbf{x}(n)}{2\pi} = \frac{1}{2\pi} \int_{-\pi}^{\pi} X_d(\omega) e^{i\omega n} d\omega$$

$$\mathbf{x}(n-10) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X_d(\omega) e^{-i\omega 10} e^{i\omega n} d\omega$$

Fact 14.1.

$$x(n-k) \xleftarrow{DTFT} X_d(\omega) e^{-i\omega k}$$
 
$$DTFT[x(n)] = \sum_{k=-\infty}^{\infty} x(k) DTFT[\delta(n-k)] = \sum_{k=-\infty}^{\infty} x(k) e^{-i\omega k}$$

The forward, or analysis, DTFT is defined as:

$$X_d(\omega) = \sum_{n = -\infty}^{\infty} x(n)e^{-i\omega n}$$

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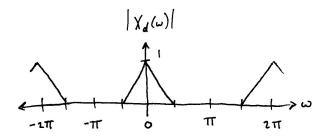


Figure 14.3: Frequency response of x(n)

Previously, we have seen the synthesis DTFT:

$$x(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X_d(\omega) e^{i\omega n} d\omega$$

**Example 14.1.** Find the DTFT[ $x(n)e^{iw_0n}$ ],  $w_0 = \frac{\pi}{6}$  if  $X_d(\omega)$  is shown in Fig. 14.3.

$$Y_d(\omega) = \sum_{n=-\infty}^{\infty} x(n)e^{i\pi/6n}e^{-i\omega n} = \sum_{n=-\infty}^{\infty} x(n)e^{-i(\omega-\pi/6)n} = X_d(\omega - \pi/6)$$

$$Y_d(\omega) = X_d(\omega - \pi/6)$$

$$Y_d(\omega) = \sum_{n=-\infty}^{\infty} y(n)e^{-i\omega n}$$

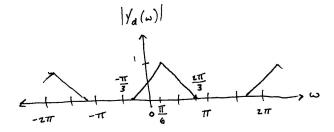


Figure 14.4: Frequency response of y(n)

Exercise 14.1. Find the  $DTFT[x(n)\cos(\frac{\pi}{6}n)]$  and plot it. Hint:  $\cos(\theta) = \frac{1}{2}(e^{i\theta} + e^{-i\theta})$ . Not all signals can have a DTFT. The sum must be finite.

Exercise 14.2. Here are some signals to practice working with the DTFT and DFT:

- Find the DTFT of  $x(n) = \alpha^n u(n), \alpha = 0.8$
- Find the IDTFT of the Ideal low-pass filter.

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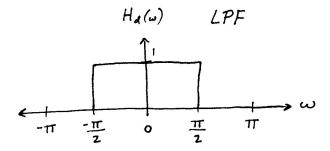


Figure 14.5: Frequency response of ideal low-pass filter with cutoff at  $\omega = \pi/2$ .

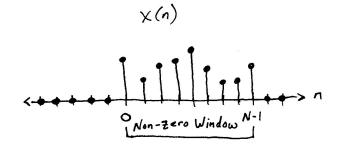


Figure 14.6: Finite length signal x(n) to pass to DFT

## 14.5 DTFT and DFT

DTFT applies to infinitely long signals that are not practical to implement. DFT is a way of addressing this problem.

We consider only [0, 1, ..., N-1] as the domain of x(n). Clearly, this is related to the DFS representation of the periodic extension of x(n).

$$\{x(n)\}_{n=0}^{N-1} \stackrel{\text{DFT}}{\longleftrightarrow} \{X(k)\}_{k=0}^{N-1}$$

$$\underline{x}^N \stackrel{\text{DFT}}{\longleftrightarrow} \underline{X}^N$$

Analysis:

$$X(k), k = [0, 1, \dots, N - 1] = \sum_{n=0}^{N-1} x(n)e^{-i\omega_0 nk}, \omega_0 = \frac{2\pi}{N}$$
$$X(k) = \sum_{n=0}^{N-1} x(n)e^{-i\frac{2\pi}{N}nk}$$

Synthesis:

$$x(n), n = [0, 1, \dots, N - 1] = \frac{1}{N} \sum_{k=0}^{N-1} X(k) e^{i\frac{2\pi}{N}kn}$$

The DFT is used a lot in practice because of its discrete nature in both the time and frequency domains. Restricting the input to a finite length can also be thought of as treating the signal as being periodic. This is only a first glance at the topic of DFT, but will hopefully serve as a reference point for the guest lecture by Professor Lustig on Tuesday.