ELEC 221 Lecture 06 Introducing filters

Tuesday 27 September 2022

Announcements

- Assignment 2 due tomorrow
- Assignment 3 available tomorrow
- Quiz 3 today

We explored periodic DT complex exponential signals:

$$\chi[n] = e^{j\omega n} = e^{j\frac{2\pi}{N}n}$$

We found that these signals behave differently than CT signals...

Difference 1: we only need to consider ω in the range $[0, 2\pi)$.

where to consider
$$\omega$$
 in the range $x[n] = e \int_{\omega}^{\omega} (\omega + 2\pi) n$

$$= e \int_{\omega}^{\omega} (\omega + 2\pi) n$$

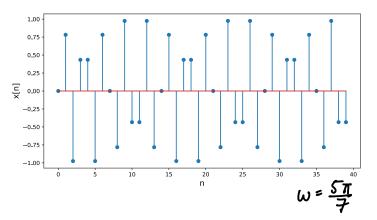
Difference 2: there are additional criteria for periodicity.

$$x[n+N] = e^{j\omega}(n+N)$$

$$= e^{j\omega n} \cdot e^{j\omega N}$$

$$= e^{j\omega n} \cdot \omega N = 2\pi m$$

Example: $x[n] = \sin(5\pi n/7)$ is periodic.

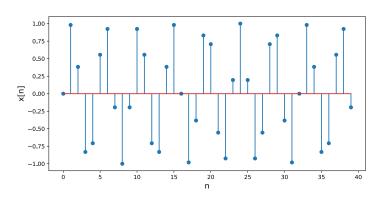


In CT, period of
$$x(t) = \sin(5\pi t/7)$$
 is $T = 14/5$.
In DT, period of $x[n] = \sin(5\pi n/7)$ is $N = 14$.

$$\frac{5\pi n}{2} = 2\pi m$$

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Example: $x[n] = \sin(5n/7)$ is NOT periodic.



In CT, period of
$$x(t) = \sin(5t/7)$$
 is $T = 14\pi/5$.

Difference 3: there are only finitely many harmonics.

ere are only finitely many harmonics.

$$\begin{array}{lll}
x_{0}[n] &= 1 \\
x_{1}[n] &= e^{j\frac{2\pi}{N}n} \\
x_{2}[n] &= e^{j\frac{2\cdot 2\pi}{N}n} \\
x_{2}[n] &= e^{j\frac{2\cdot 2\pi}{N}n} \\
x_{N-1}[n] &= e^{j\frac{2\cdot 2\pi}{N}n} \\
x_{N-1}[n] &= e^{j\frac{2\cdot 2\pi}{N}n} \\
x_{N-1}[n] &= e^{j\frac{2\pi}{N}n} \\
x_{N-1}[n] &= e^{j\frac{N}$$

We expressed DT complex exponential signals with fundamental period N as Fourier series.

DT synthesis equation:

$$\times [n] = \sum_{k=0}^{N-1} C_k e^{jk \cdot \frac{2\pi}{N}n}$$

DT analysis equation:

$$Ck = \frac{1}{N} \sum_{n=0}^{N-1} x(n) e^{-jk \frac{2\pi n}{N}}$$

We introduced the idea of **system functions** and **frequency response** of LTI systems.

$$x(t) \rightarrow y(t) = \sum_{k=-\infty}^{\infty} c_k H(jkw)e^{jkwt}$$

$$x[n] \rightarrow y[n] = \sum_{k=0}^{\infty-1} c_k H(e^{jkw}) e^{jkwn}$$

 $H(j\omega)$ in CT, and $H(e^{j\omega})$ in DT, are called the **frequency** response of the system.

Today

This week, we are going to look at our first major application of signals and systems: filters.

Learning outcomes:

- Define filters and identify a basic set of ideal frequency-selective filters
- Plot the frequency response of a filter in CT and DT
- Define and distinguish between finite-impulse-response (FIR)
 and infinite-impulse-response (IIR) filters in DT

In-class activity on Thursday: apply filters in the context of audio processing.

Filters

Filters are LTI systems that can be used to separate out, combine, or modify the components of a signal at specific frequencies.

Two key types:

- **Frequency-shaping**: change the amplitudes of parts of a signal at specified frequencies
- Frequency-selective: eliminate or attentuate parts of a signal at specified frequencies

A convenient way to understand (and to design) filters is by looking at their **frequency response**.

Recall that the **system function** of a CT system $H(j\omega)$, is a measure of how much a system "modifies" a particular frequency:

$$x(t) = \sum_{k=-\infty}^{\infty} c_k e^{jkwt}$$
, $y(t) = \sum_{k=-\infty}^{\infty} c_k H(jkw) e^{jkwt}$

By selecting the frequency response at will, we can change the behaviour of a system.

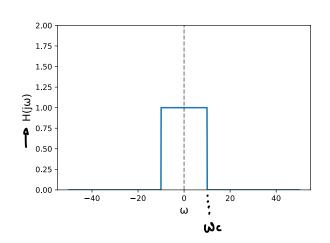
Example. Consider a system function defined as follows.

What does this look like, and what does it do?

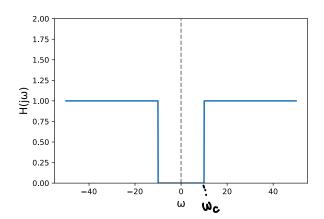
This is an ideal lowpass filter.



We often represent the frequency response graphically:

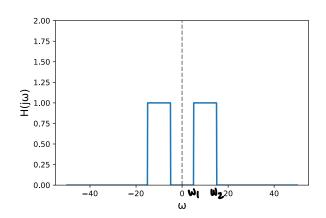


We can also consider an ideal highpass filter:



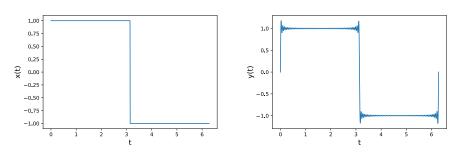
Or an ideal bandpass filter:

$$H(jw) = \begin{cases} 1 & w_1 \leq |w| \leq w_2 \\ 0 & \text{otherwise} \end{cases}$$



Filters and ringing

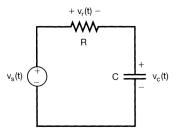
We have inadvertently already encountered an example of what can happen when we apply a lowpass filter: the Gibbs phenomenon.



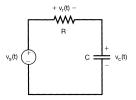
We can actually reduce the effect of the Gibbs phenomenon using a different kind of frequency response called σ approximation.

In reality some filters are made up of real, physical components, described by differential equations, and involve tradeoffs in their construction.

Example: We can construct a lowpass filter using a resistor and a capacitor.



Suppose we input some complex exponential signal $v_s(t) = e^{j\omega t}$



Can derive two expressions for the current, using the resistor and capacitor respectively:

$$i(t) = \frac{v_s(t) - v_c(t)}{R}$$

$$i(t) = C \frac{dv_c(t)}{dt}$$

Image credit: Oppenheim chapter 3.10.

Put these together to form a differential equation:

$$C \frac{dv_c(t)}{dt} = \frac{v_s(t) - v_c(t)}{R}$$

$$RC \frac{dv_c(t)}{dt} + v_c(t) = v_s(t)$$

What is the voltage across the capacitor?

Can show that if $v_s(t)=e^{j\omega t}$, then $\mathbf{V_C(t)}=\mathbf{H(jw)}$ for some scaling $H(j\omega)$.

Plug this into the ODE:

RC
$$\frac{dV_{c}(t)}{dt} + V_{c}(t) = V_{s}(t)$$

RC $\frac{dV_{c}(t)}{dt} + V_{c}(t) = V_{s}(t)$

RC $\frac{d}{dt} (H(j\omega)e^{j\omega t}) + H(j\omega)e^{j\omega t} = e^{j\omega t}$

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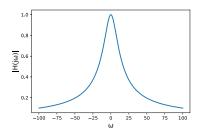
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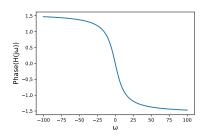
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Results in the following frequency response (setting RC = 0.1):





Adjusting the value of RC controls the frequency response. Increasing RC cuts off more frequencies.

However, there are tradeoffs involved in the design of such filters.

Example: we want the system to response *quickly* when we start giving it input. How does it respond to the unit step?

You can show that the unit impulse response of this filter is

$$h(t) = \frac{1}{RC} e^{-t/RC} u(t)$$

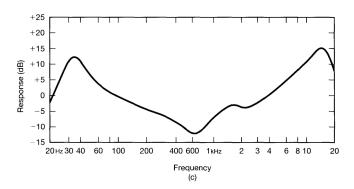
and the unit step response is

$$S(t) = \int_{-\infty}^{t} h(\tau) d\tau = (1 - e^{-\tau}) u(t)$$

High RC means tight frequency response, but slow step response.

Frequency shaping filters

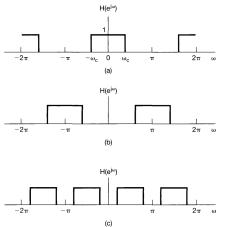
Especially common in audio process: not eliminating any frequencies, just changing their strengths.



Decibels are units of $20\log_{10}|H(j\omega)|$; frequency in Hz is $\omega/2\pi$. (We will play with these on Thursday!)

DT filters

Recall that in DT, the frequency increases up until $\omega=\pi$, then decreases as it approaches 2π .



DT filters

There are two major categories of DT filters:

- 1. Infinite impulse response (IIR)
- 2. Finite impulse response (FIR)

$$y[n] = a \cdot y(n-1) + x[n]$$

Example: we can generate a low- or high-pass filter using a system described by a first-order difference equation.

$$y[n] - ay[n-i] = x[n]$$

We can use the same method as in the CT case to compute the frequency response: we know that complex exponential signals are eigenfuctions, so $y[n] = H(e^{j\omega})e^{j\omega n}$.

$$x(n) = e^{j\omega n}$$
 $y(n) = H(e^{j\omega}) \cdot e^{j\omega n}$

Work through the math:

through the math:
$$y(n) - \alpha y[n-1] = x[n]$$

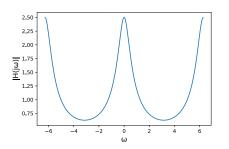
$$H(e^{j\omega}) e^{j\omega n} - \alpha \cdot H(e^{j\omega}) e^{j\omega (n-1)} = e^{j\omega n}$$

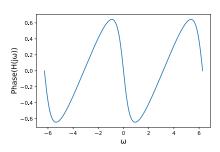
$$H(e^{j\omega}) (1 - \alpha e^{-j\omega}) e^{j\omega n} = e^{j\omega n}$$

$$H(e^{j\omega}) = \frac{1}{1 - \alpha e^{-j\omega}}$$

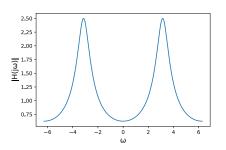
Depending on the value of a, this could be either a highpass or lowpass filter.

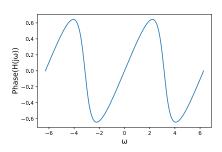
Case: a > 0





Case: a < 0





What happens to the impulse response of this filter? Need to solve the differential equation... consider a signal $x[n] = K\delta[n]$.

$$y(n) - ay(n-1) = x(n) = K \cdot \delta[n]$$

Assuming the system starts at rest (y[-1] = 0), we can solve recursively:

$$y[0] = x[0] = K \cdot \delta[0] = K$$

 $y[1] = ay[0] + x[1] = aK + K \cdot \delta[1] = aK$
 $y[2] = ay[1] + x[2] = a^2K + K \cdot \delta[2] = a^2K$
 $y[n] = ay[n-1] + x[n] = a^nK$

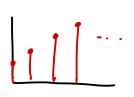
If we put in the unit impulse (K=1), we get

$$y[0] = 1$$

$$y[1] = a$$

$$y[2] = a^{2}$$

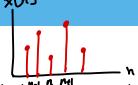
$$y[n] - a^{n}$$



so the impulse response is

$$h[n] = a^n \cdot u[n]$$

This system has an infinite impulse response!



An example of a DT filter with a finite impulse response is the moving average.

Suppose the output of the system is moving after in a window of size M around each point:

$$y[n] = \frac{1}{2M+1} \sum_{k=-M}^{M} x[n-k]$$

What is its impulse response and frequency response?

Impulse response: set
$$x[n] = \delta[n]$$

$$h(n) = \frac{1}{2M+1} \sum_{k=-M}^{M} S(n-k)$$

$$\frac{1}{2M+1}$$

This is clearly finite (as a result: these filters are stable systems).

Frequency response: set $x[n] = e^{j\omega n}$,

$$y[n] = \frac{1}{2M+1} \sum_{k=-M}^{M} e^{j\omega(n-k)}$$
$$= \frac{1}{2M+1} \sum_{k=-M}^{M} e^{-j\omega k} \cdot e^{j\omega n}$$
$$= H(e^{j\omega})e^{j\omega}$$

So

$$H(e^{j\omega}) = \frac{1}{2M+1} \sum_{k=-M}^{M} e^{-j\omega k}$$

What does this look like? Let's plot it...

Recap

Today's learning outcomes were:

- Define filters and identify a basic set of ideal frequency-selective filters
- Plot the frequency response of a filter in CT and DT
- Define and distinguish between finite-impulse-response (FIR) and infinite-impulse-response (IIR) filters in DT

What topics did you find unclear today?

For next time

Content:

- Fun with filters! In-class activity with opportunity for extra credit.
- To prepare for class:
 - Produce a 10-15s clip of your favourite song in .wav format
 - Set up a Python environment (Google Colab works fine)
 - Loosely organize yourselves into groups of 3-4 (it will help for at least one person to have musical training)

Action items:

- 1. Assignment 2 is due tomorrow at 23:59
- 2. Assignment 3 is available tomorrow

h-M

Recommended reading:

- From today's class: Oppenheim 3.9-3.12
- For next class: Oppenheim 5.0-5.3