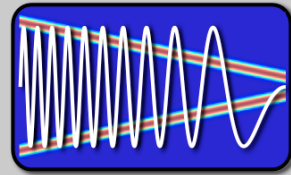


EE123



Digital Signal Processing

Lecture 8

based on slides by J.M. Kahn

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Announcements

- Last time:
 - FFT
- Today Frequency Analysis with DFT
- Read Ch. 10.1-10.2

- Who started playing with the SDR?

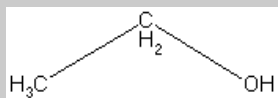
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What is this?



The first NMR spectrum of ethanol 1951.



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Spectral Analysis with the DFT

The DFT can be used to analyze the spectrum of a signal.

It would seem that this should be simple, take a block of the signal and compute the spectrum with the DFT.

However, there are many important issues and tradeoffs:

- Signal duration vs spectral resolution
- Signal sampling rate vs spectral range
- Spectral sampling rate
- Spectral artifacts

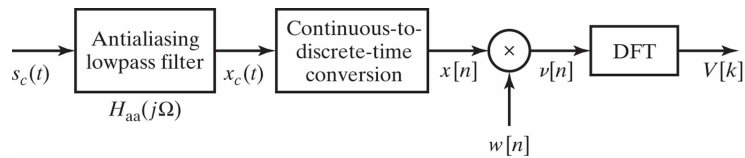
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Spectral Analysis with the DFT

Consider these steps of processing continuous-time signals:



Spectral Analysis with the DFT

Two important tools:

- Applying a window to the input signal – reduces spectral artifacts
- Padding input signal with zeros – increases the spectral sampling

Key Parameters:

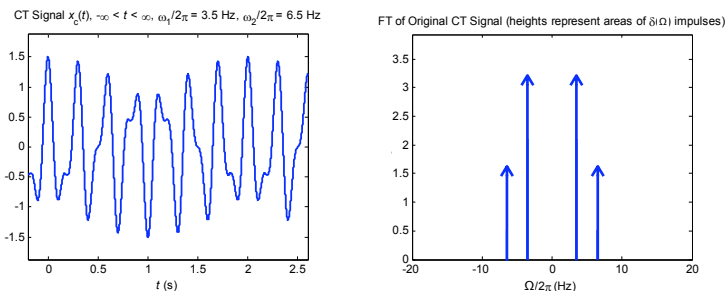
Parameter	Symbol	Units
Sampling interval	T	s
Sampling frequency	$\Omega_s = \frac{2\pi}{T}$	rad/s
Window length	L	unitless
Window duration	$L \cdot T$	s
DFT length	$N \geq L$	unitless
DFT duration	$N \cdot T$	s
Spectral resolution	$\frac{\Omega_s}{L} = \frac{2\pi}{L \cdot T}$	rad/s
Spectral sampling interval	$\frac{\Omega_s}{N} = \frac{2\pi}{N \cdot T}$	rad/s

Filtered Continuous-Time Signal

We consider an example:

$$x_c(t) = A_1 \cos \omega_1 t + A_2 \cos \omega_2 t$$

$$X_c(j\Omega) = A_1 \pi [\delta(\Omega - \omega_1) + \delta(\Omega + \omega_1)] + A_2 \pi [\delta(\Omega - \omega_2) + \delta(\Omega + \omega_2)]$$



Sampled Filtered Continuous-Time Signal

Sampled Signal

If we sampled the signal over an infinite time duration, we would have:

$$x[n] = x_c(t)|_{t=nT}, \quad -\infty < n < \infty$$

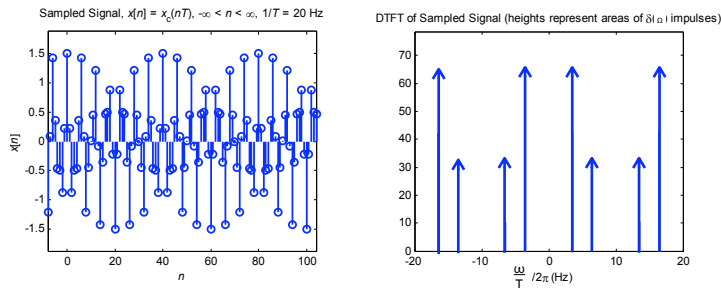
described by the discrete-time Fourier transform:

$$X(e^{j\Omega T}) = \frac{1}{T} \sum_{r=-\infty}^{\infty} X_c \left(j \left(\Omega - r \frac{2\pi}{T} \right) \right), \quad -\infty < \Omega < \infty$$

Recall $X(e^{j\omega}) = X(e^{j\Omega T})$, where $\omega = \Omega T$... more in ch 4.

Sampled Filtered Continuous-Time Signal

In the examples shown here, the sampling rate is $\Omega_s/2\pi = 1/T = 20$ Hz, sufficiently high that aliasing does not occur.



Windowed Sampled Signal

Block of L Signal Samples

In any real system, we sample only over a finite block of L samples:

$$x[n] = x_c(t)|_{t=nT}, \quad 0 \leq n \leq L-1$$

This simply corresponds to a rectangular window of duration L .

Recall: in Homework 1 we explored the effect of rectangular and triangular windowing

Windowed Sampled Signal

Windowed Block of L Signal Samples

We take the block of signal samples and multiply by a window of duration L , obtaining:

$$v[n] = x[n] \cdot w[n], \quad 0 \leq n \leq L-1$$

Suppose the window $w[n]$ has DTFT $W(e^{j\omega})$.

Then the windowed block of signal samples has a DTFT given by the periodic convolution between $X(e^{j\omega})$ and $W(e^{j\omega})$:

$$V(e^{j\omega}) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X(e^{j\theta}) W(e^{j(\omega-\theta)}) d\theta$$

Windowed Sampled Signal

Convolution with $W(e^{j\omega})$ has two effects in the spectrum:

- 1 It limits the spectral resolution. – Main lobes of the DTFT of the window
- 2 The window can produce *spectral leakage*. – Side lobes of the DTFT of the window

* These two are always a tradeoff - time-frequency uncertainty principle

Windows (as defined in MATLAB)

Name(s)	Definition	MATLAB Command	Graph ($M = 8$)
Rectangular Boxcar Fourier	$w[n] = \begin{cases} 1 & n \leq M/2 \\ 0 & n > M/2 \end{cases}$	<code>boxcar(M+1)</code>	
Triangular	$w[n] = \begin{cases} 1 - \frac{ n }{M/2+1} & n \leq M/2 \\ 0 & n > M/2 \end{cases}$	<code>triang(M+1)</code>	
Bartlett	$w[n] = \begin{cases} 1 - \frac{ n }{M/2} & n \leq M/2 \\ 0 & n > M/2 \end{cases}$	<code>bartlett(M+1)</code>	

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Windows (as defined in MATLAB)

Name(s)	Definition	MATLAB Command	Graph ($M = 8$)
Hann	$w[n] = \begin{cases} \frac{1}{2} \left[1 + \cos\left(\frac{\pi n}{M/2}\right) \right] & n \leq M/2 \\ 0 & n > M/2 \end{cases}$	<code>hann(M+1)</code>	
Hanning	$w[n] = \begin{cases} \frac{1}{2} \left[1 + \cos\left(\frac{\pi n}{M/2+1}\right) \right] & n \leq M/2 \\ 0 & n > M/2 \end{cases}$	<code>hanning(M+1)</code>	
Hamming	$w[n] = \begin{cases} 0.54 + 0.46 \cos\left(\frac{\pi n}{M/2}\right) & n \leq M/2 \\ 0 & n > M/2 \end{cases}$	<code>hamming(M+1)</code>	

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Windows

- All of the window functions $w[n]$ are real and even.
- All of the discrete-time Fourier transforms

$$W(e^{j\omega}) = \sum_{n=-\frac{M}{2}}^{\frac{M}{2}} w[n] e^{-jn\omega}$$

are real, even, and periodic in ω with period 2π .

- In the following plots, we have normalized the windows to unit d.c. gain:

$$W(e^{j0}) = \sum_{n=-\frac{M}{2}}^{\frac{M}{2}} w[n] = 1$$

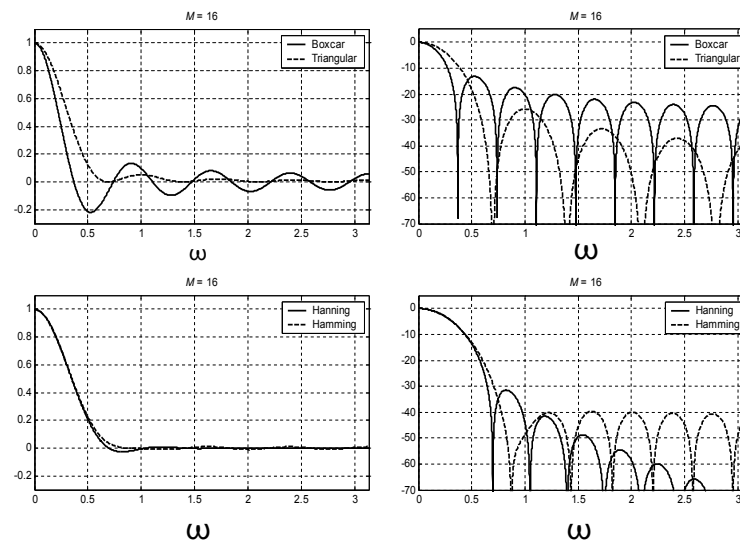
This makes it easier to compare windows.

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Window Example



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