Fall 2011, EE123 Digital Signal Processing

Lecture 7 (chap 10.1-10.2)

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Spectral Analysis with the DFT

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

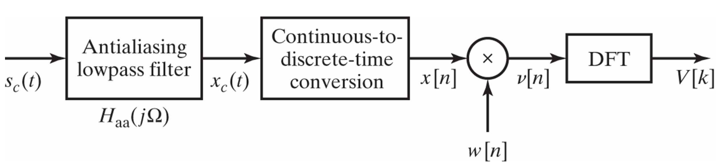
It would seem that this should be simple, take a block of the signal and compute the spectrum with the DFT.

However, there are many important issues and tradeoffs:

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

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

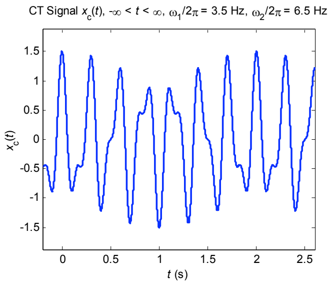
Key Parameters:

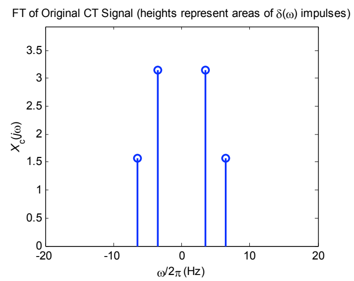
Parameter	**Symbol**	**Units**
Sampling interval	T	s
Sampling frequency	$\omega_s = \frac{2\pi}{T}$	rad/s
Window length	L	unitless
Window duration	$L \cdot T$	s
DFT length	$N \geq L$	unitless
DFT duration	$N \cdot T$	s
Spectral resolution	$\frac{\omega_s}{L} = \frac{2\pi}{L \cdot T}$	rad/s
Spectral sampling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

Filtered Continuous-Time Signal

We consider an example:

$$\begin{aligned} x_c(t) &= A_1 \cos \omega_1 t + A_2 \cos \omega_2 t \\ X_c(j\omega) &= A_1 \pi [\delta(\omega - \omega_1) + \delta(\omega + \omega_1)] + A_2 \pi [\delta(\omega - \omega_2) + \delta(\omega + \omega_2)] \end{aligned}$$





Sampled Filtered Continuous-Time Signal

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

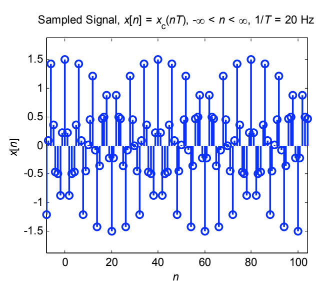
$$x[n] = x_c(t)|_{t=nT}, \quad -\infty < n < \infty$$

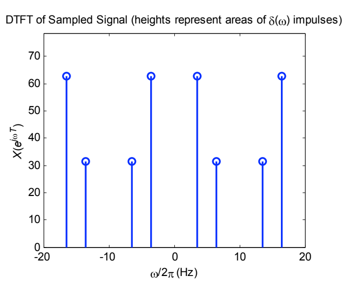
described by the discrete-time Fourier transform:

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

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:

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

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:

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

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

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

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

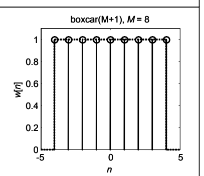
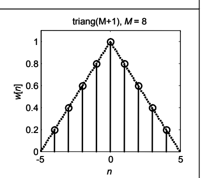
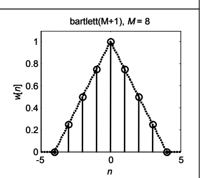
Windowed Sampled Signal

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

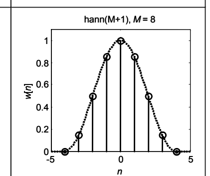
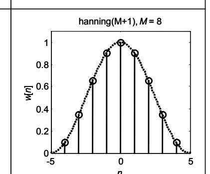
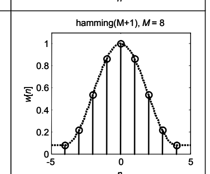
1. It limits the spectral resolution. – Main lobes of the DTFT of the window
2. The window can produce *spectral leakage*. – Side lobes of the DTFT of the window

* 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	$w[n] = \begin{cases} 1 & \lvert n\rvert \le M/2 \\ 0 & \lvert n\rvert > M/2 \end{cases}$	`boxcar(M+1)`	
Triangular	$w[n] = \begin{cases} 1 - \frac{\lvert n\rvert}{M/2+1} & \lvert n\rvert \le M/2 \\ 0 & \lvert n\rvert > M/2 \end{cases}$	`triang(M+1)`	
Bartlett	$w[n] = \begin{cases} 1 - \frac{\lvert n\rvert}{M/2} & \lvert n\rvert \le M/2 \\ 0 & \lvert n\rvert > M/2 \end{cases}$	`bartlett(M+1)`	

Windows (as defined in MATLAB)

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

Windows

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

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

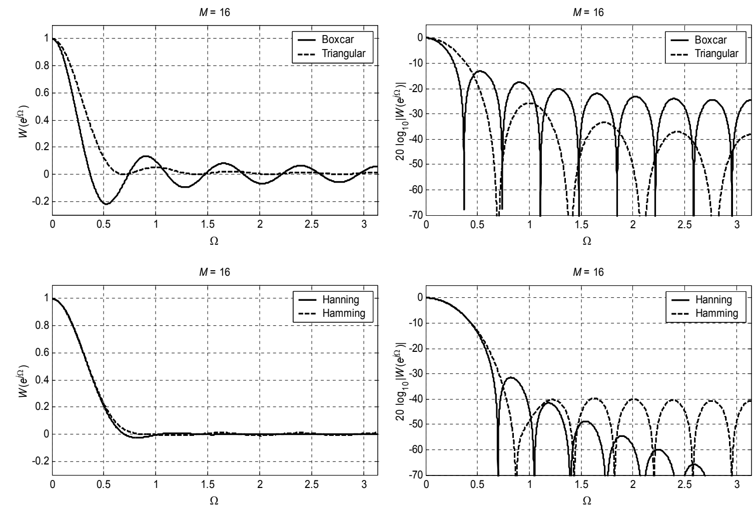
are real, even, and periodic in ω with period 2π.

- 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.

Window Example



Windows Properties

These are characteristic of the window type

Window	Main-lobe	Sidelobe δ_s	Sidelobe $-20\log_{10}\delta_s$
Rect	$\frac{4\pi}{M+1}$	0.09	21
Bartlett	$\frac{8\pi}{M+1}$	0.05	26
Hann	$\frac{8\pi}{M+1}$	0.0063	44
Hamming	$\frac{8\pi}{M+1}$	0.0022	53
Blackman	$\frac{12\pi}{M+1}$	0.0002	74

Most of these (Bartlett, Hann, Hamming) have a transition width that is twice that of the rect window.

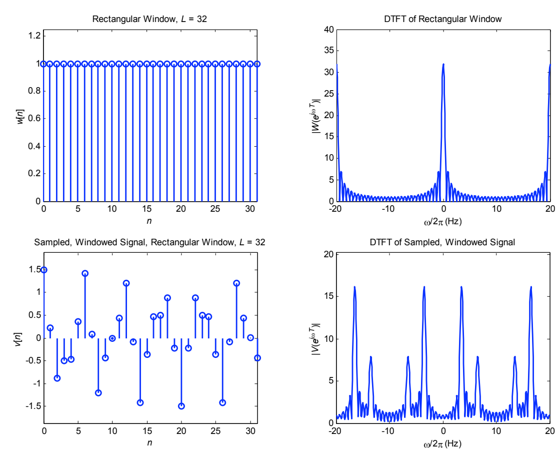
Warning: Always check what's the definition of M

Adapted from *A Course In Digital Signal Processing* by Boaz Porat, Wiley, 1997

Windows Examples

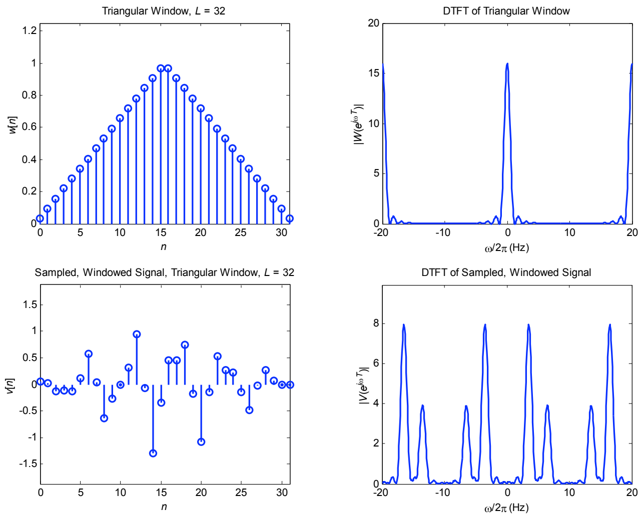
Here we consider several examples. As before, the sampling rate is $\omega_s/2\pi = 1/T = 20$ Hz.

Rectangular Window, $L = 32$



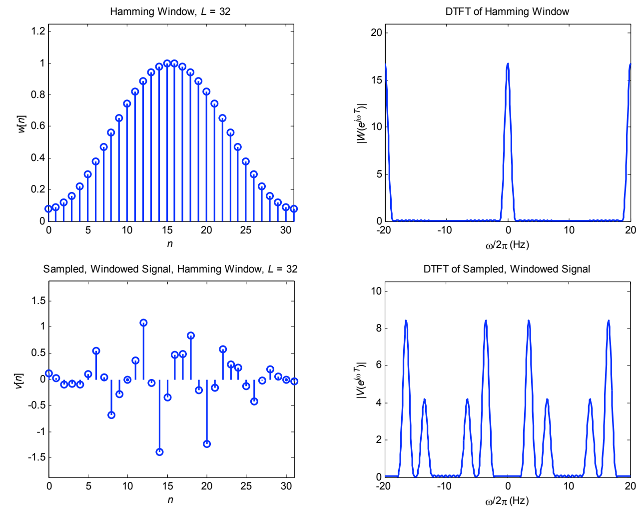
Windows Examples

Triangular Window, $L = 32$



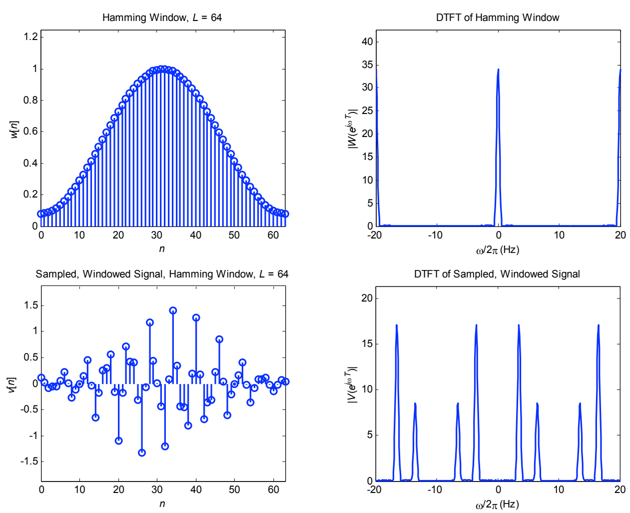
Windows Examples

Hamming Window, $L = 32$



Windows Examples

Hamming Window, $L = 64$



Zero-Padding

- In preparation for taking an N-point DFT, we may zero-pad the windowed block of signal samples to a block length $N \geq L$:

$$\begin{cases} v[n] & 0 \leq n \leq L-1 \\ 0 & L \leq n \leq N-1 \end{cases}$$

- This zero-padding has no effect on the DTFT of $v[n]$, since the DTFT is computed by summing over $-\infty < n < \infty$.

Effect of Zero Padding

- We take the N-point DFT of the zero-padded $v[n]$, to obtain the block of N spectral samples:

$$V[k], \quad 0 \leq k \leq N-1$$

Zero-Padding

- Consider the DTFT of the zero-padded $v[n]$. Since the zero-padded $v[n]$ is of length N, its DTFT can be written:

$$V(e^{j\omega T}) = \sum_{n=0}^{N-1} v[n]e^{-jn\omega T}, \qquad -\infty < \omega < \infty$$

The N-point DFT of $v[n]$ is given by:

$$V[k] = \sum_{n=0}^{N-1} v[n]W_N^{kn} = \sum_{n=0}^{N-1} v[n]e^{-j(2\pi/N)nk}, \qquad 0 \le k \le N-1$$

We see that $V[k]$ corresponds to the samples of $V(e^{j\omega T})$:

$$V[k] = V(e^{j\omega T})\Big|_{\omega = k\frac{2\pi}{NT}}, \qquad 0 \le k \le N-1$$

To obtain samples at more closely spaced frequencies, we zero-pad $v[n]$ to longer block length N. The spectrum is the same, we just have more samples.

Frequency Analysis with DFT

- Note that the ordering of the DFT samples is unusual.

$$V[k] = \sum_{n=0}^{N-1} v[n]W_N^{nk}$$

The DC sample of the DFT is $k = 0$

$$V[0] = \sum_{n=0}^{N-1} v[n]W_N^{0n} = \sum_{n=0}^{N-1} v[n]$$

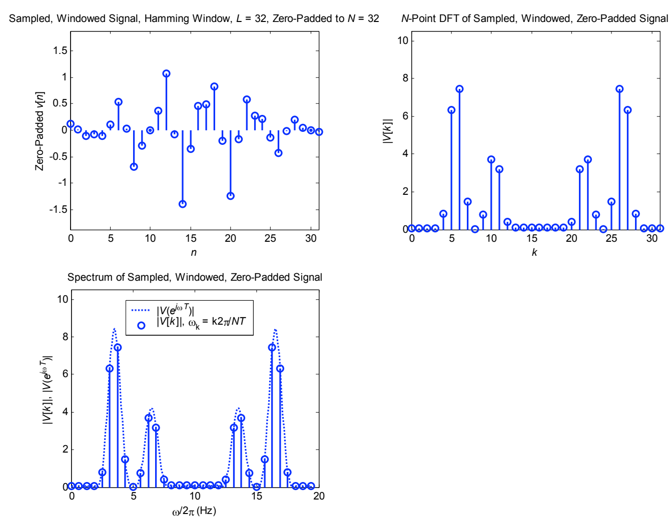
- The positive frequencies are the first $N/2$ samples
- The first $N/2$ negative frequencies are circularly shifted

$$((-k))_N = N - k$$

so they are the last $N/2$ samples. (Use `fftshift` to reorder)

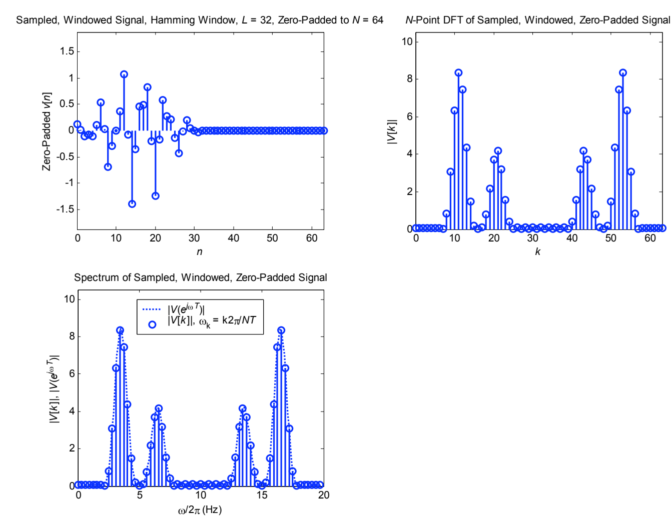
Frequency Analysis with DFT Examples:

Hamming Window, $L = 32$, $N = 32$



Frequency Analysis with DFT Examples:

Hamming Window, $L = 32$, Zero-Padded to $N = 64$



Frequency Analysis with DFT

- Length of window determines spectral resolution
- Type of window determines side-lobe amplitude. (Some windows have better tradeoff between resolution-sidelobe)
- Zero-padding approximates the DTFT better. Does not introduce new information!

Potential Problems and Solutions

Potential Problems and Solutions

Problem	Possible Solutions
1. Spectral error from aliasing	a. Filter signal to reduce frequency content above $\omega_s/2 = \pi/T$. b. Increase sampling frequency $\omega_s = 2\pi/T$.
2. Insufficient frequency resolution.	a. Increase $L \cdot T$, usually by increasing L while keeping T fixed. b. Use window having narrow main lobe.
3. Spectral error from leakage	a. Use window having low side lobes. b. Increase $L \cdot T$, usually by increasing L while keeping T fixed.
4. Missing features due to spectral sampling.	a. Increase $L \cdot T$, usually by increasing L while keeping T fixed. b. Increase $N \cdot T$ by zero-padding $v[n]$ to length $N > L$.

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Time-Dependent Fourier Transform

Also called Short-time Fourier Transform

Time-Dependent Fourier Transform

$$X[n,\lambda] = \sum_{m=-\infty}^{\infty} x[n+m]w[m]e^{-j\lambda m}$$

This is a mapping of 1D discrete signal to 2D. Where: n- discrete, λ-continuous.

Equivalent to sliding a window and computing the DTFT.

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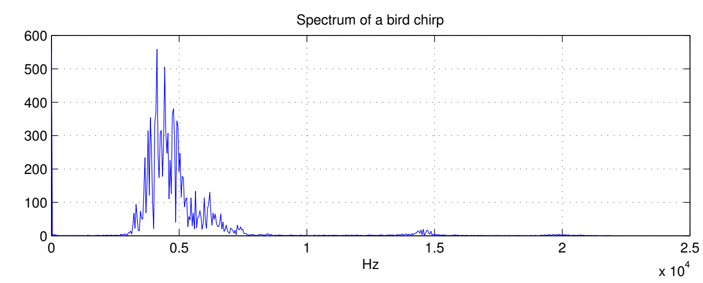
Example: Bird Chirp

Play Sound!



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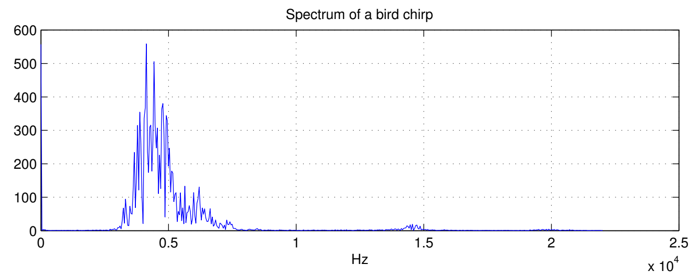
Example: Bird Chirp

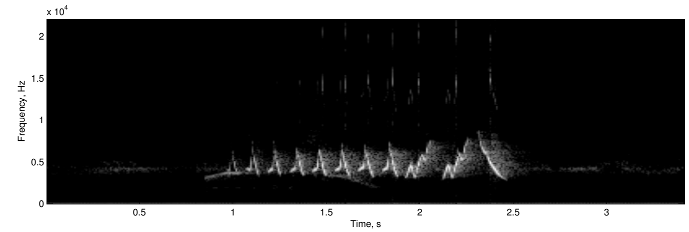
Play Sound!



No temporal information!

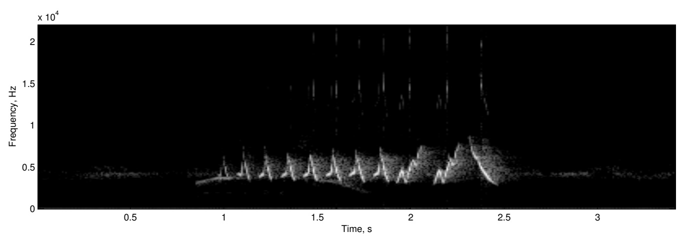
Example: Bird Chirp

Instead, use Time-Dependent Fourier Transform. Plot as a spectrogram.



Example: Bird Chirp

Instead, use Time-Dependent Fourier Transform. Plot as a spectrogram.



Trade-off between temporal and spectral resolution.

Sampling the Time-Dependent Fourier Transform using DFT

Sampling the TD-DTFT

$$X_r[k] = \sum_{m=0}^{L-1} x[rR+m]w[m]e^{-j(2\pi N)km}$$

- L - is the window length
- R - jumps of samples in time
- N - number of DFT samples

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