

Lecture 10

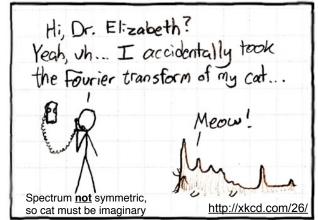
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Announcements

- · Midterm: Friday next week
 - Open everything
 - -... but cheat sheet recommended instead
 - Who can not stay till 5pm?
- Optional homework next week
 - Will give you midterm and practice questions
- · How's lab I going?

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How do you know this guy is insane?



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Last Time

- · Frequency Analysis with DFT
- Windowing
- · Zero-Padding
- · Today:
 - Time-Dependent Fourier Transform
 - Heisenberg Boxes

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Discrete Transforms (Finite)

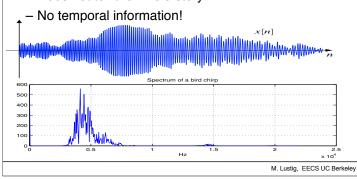
- DFT is only one out of a LARGE class of transforms
- · Used for:
 - -Analysis
 - -Compression
 - -Denoising
 - -Detection
 - -Recognition
 - -Approximation (Sparse)

Sparse representation has been one of the hottest research topics in the last 15 years in sp

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Example of spectral analysis

- Spectrum of a bird chirping
 - Interesting,.... but...
 - Does not tell the whole story



Time Dependent Fourier Transform

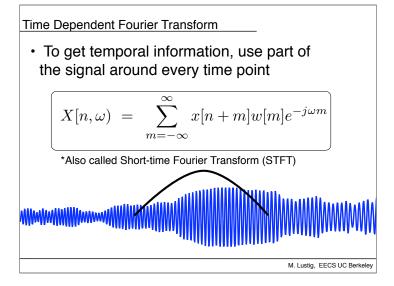
 To get temporal information, use part of the signal around every time point

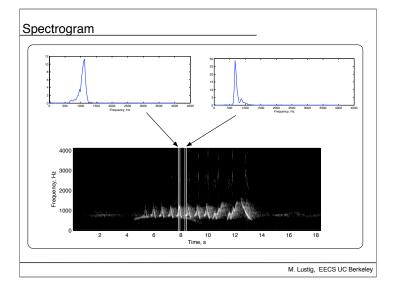
$$X[n,\omega) = \sum_{m=-\infty}^{\infty} x[n+m]w[m]e^{-j\omega m}$$

*Also called Short-time Fourier Transform (STFT)

- Mapping from 1D \Rightarrow 2D, n discrete, w cont.
- Simply slide a window and compute DTFT

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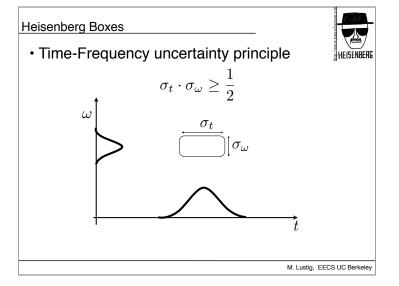


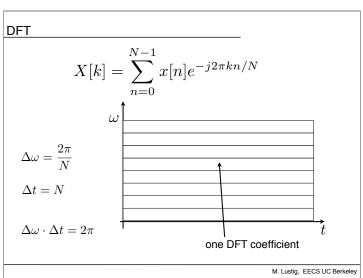
Discrete Time Dependent FT

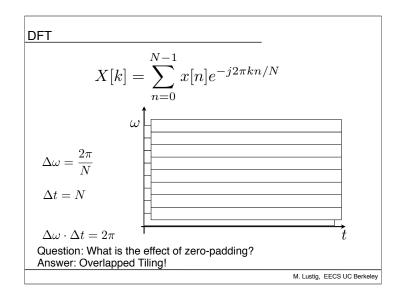
$$X_r[k] = \sum_{m=0}^{L-1} x[rR + m]w[m]e^{-j2\pi km/N}$$

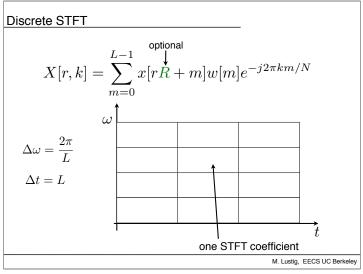
- · L Window length
- R Jump of samples
- N DFT length
- Tradeoff between time and frequency resolution

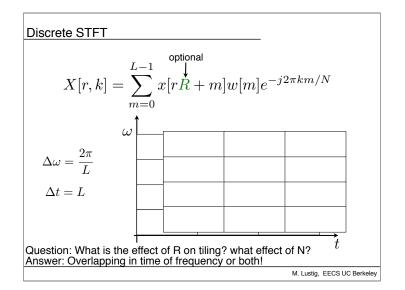
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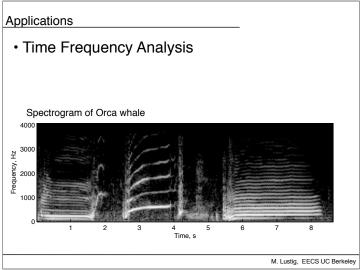


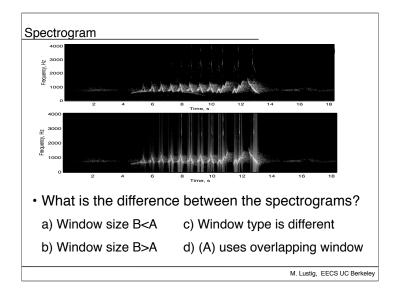


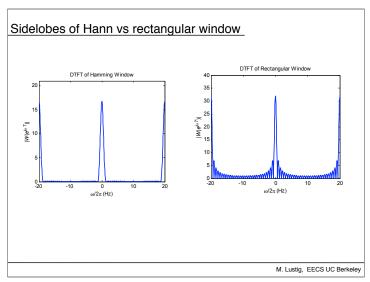


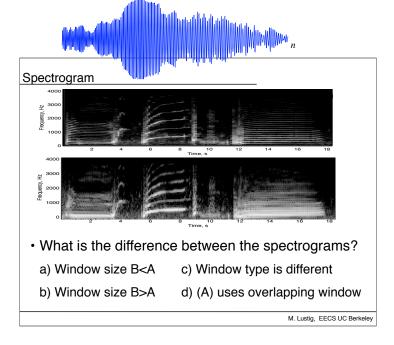


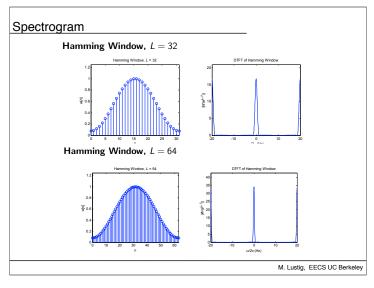


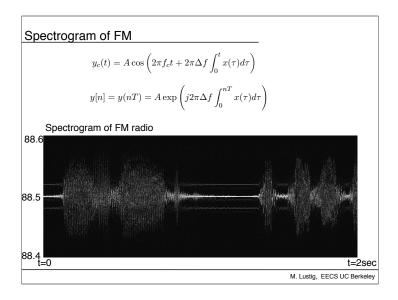


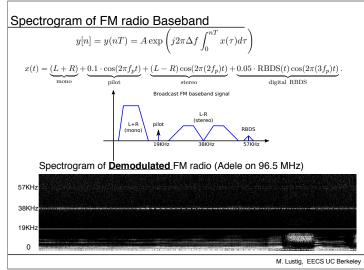


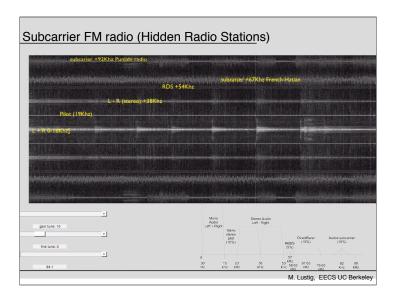


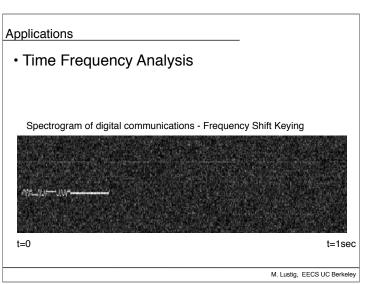












STFT Reconstruction

$$x[rR + m]w_L[m] = \frac{1}{N} \sum_{k=0}^{N-1} X[n, k] e^{j2\pi km/N}$$

• For non-overlapping windows, R=L:

$$x[n] = \frac{x[n - rL]}{w_L[n - rL]}$$
$$rL \le n \le (r+1)R - 1$$

· What is the problem?

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STFT Reconstruction

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• For non-overlapping windows, R=L:

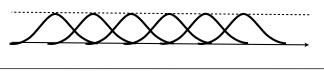
$$x[n] = \frac{x[n-rL]}{w_L[n-rL]}$$
$$rL \le n \le (r+1)R - 1$$

 For stable reconstruction must overlap window 50% (at least)

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STFT Reconstruction

- For stable reconstruction must overlap window 50% (at least)
- For Hann, Bartlett reconstruct with overlap and add. No division!



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Applications

- Noise removal
- Recall bird chirp

 Spectrum of a bird chirp

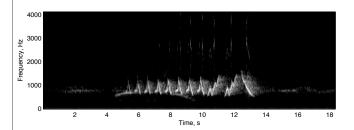
 Spectrum of a bird chirp

 Spectrum of a bird chirp

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Application

Denoising of Sparse spectrograms



 Spectrum is sparse! can implement adaptive filter, or just threshold!

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Limitations of Discrete STFT

- Need overlapping ⇒ Not orthogonal
- Computationally intensive O(MN log N)
- · Same size Heisenberg boxes

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From STFT to Wavelets

- · Basic Idea:
 - -low-freq changes slowly fast tracking unimportant
 - -Fast tracking of high-freq is important in many apps.
 - -Must adapt Heisenberg box to frequency
- Back to continuous time for a bit.....

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