

ESE 531: Digital Signal Processing

Lec 23: April 21, 2020
Wavelet Transform



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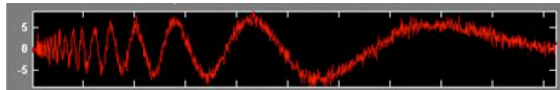
Wavelet Transform



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Motivation

- Some signals obviously have spectral characteristics that vary with time



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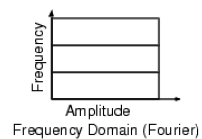
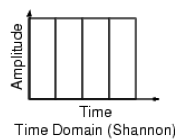
Criticism of Fourier Spectrum

- It's giving you the spectrum of the 'whole time-series'
- Which is OK if the time-series is stationary. But what if it's not?
- We need a technique that can "march along" a time series and that is capable of:
 - Analyzing spectral content in different places
 - Detecting sharp changes in spectral character

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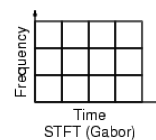
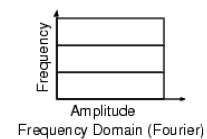
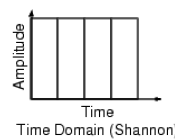
Transform Comparison



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Transform Comparison

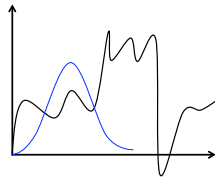


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Discrete Time-Dependent FT

- Fixed window size, shift in time (Gabor)

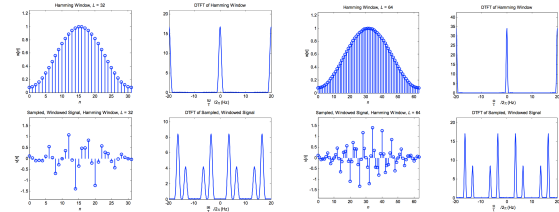


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Windowed Sampled CT Signal Example

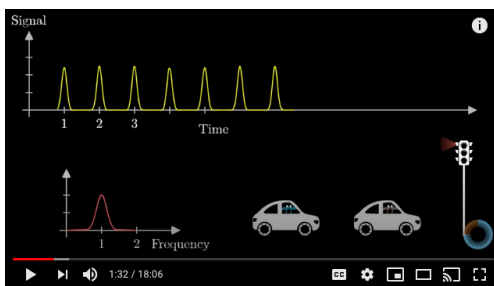
- As before, the sampling rate is $\Omega_s/2\pi = 1/T = 20\text{Hz}$
- Hamming Window, $L = 32$ vs. $L = 64$



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Uncertainty Principle



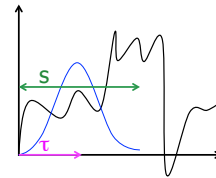
<https://youtu.be/MBnnXbOM5S4?t=49>

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Discrete Time-Dependent FT

- Fixed window size, shift in time (Gabor)

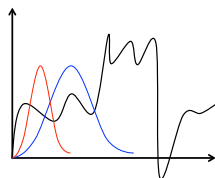


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Discrete Time-Dependent FT

- Fixed window size, shift in time (Gabor)



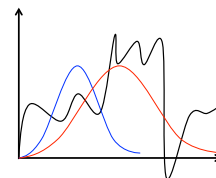
- Make the window smaller
 - Better localization
 - Less spectral resolution

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Discrete Time-Dependent FT

- Fixed window size, shift in time (Gabor)



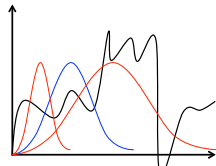
- Make the window larger
 - Worse localization
 - More spectral resolution

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Discrete Time-Dependent FT

- Fixed window size, shift in time (Gabor)

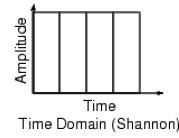


- Use a big window for low frequency content that is not localized in time
- Use a small window for high frequency content that is localized in time

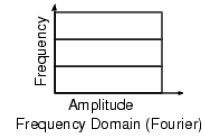
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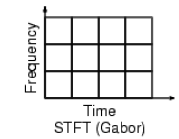
Transform Comparison



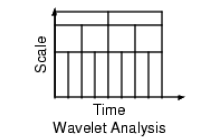
Time Domain (Shannon)



Frequency Domain (Fourier)



Time STFT (Gabor)



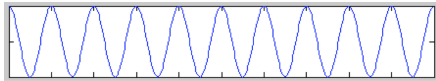
Wavelet Analysis

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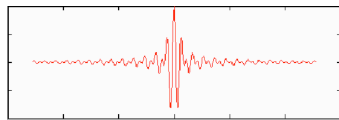
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Fourier vs. Wavelet

- Fourier Analysis is based on an indefinitely long cosine wave of a specific frequency



- Wavelet Analysis is based on a short duration wavelet of a specific center frequency



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Wavelet Transform

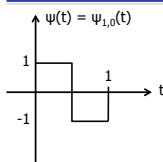
- All wavelets derived from *mother* wavelet

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t-\tau}{s}\right)$$

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Example: Haar Wavelet

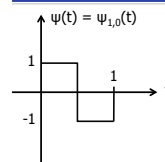


$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t-\tau}{s}\right)$$

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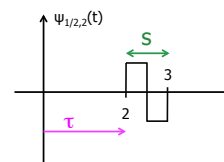
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Example: Haar Wavelet



$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t-\tau}{s}\right)$$

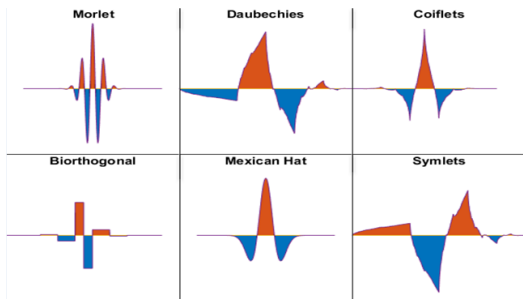
$$s=1/2, \tau=2$$



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Examples of Wavelets



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Wavelet – Scaled and Shifted

$$\Psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \Psi\left(\frac{t-\tau}{s}\right)$$

Annotations for the equation:

- normalization (points to $\frac{1}{\sqrt{s}}$)
- shift in time (points to $t - \tau$)
- change in scale (points to s)
- Mother wavelet (points to Ψ)
- wavelet with scale, s and translation, τ (points to the entire expression)

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Continuous Wavelet Transform

$$\gamma(s, \tau) = \int f(t) \Psi_{s,\tau}(t) dt$$

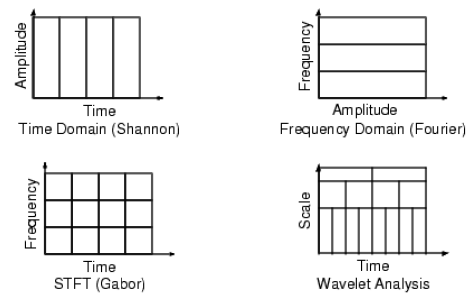
Annotations for the equation:

- time-series (points to $f(t)$)
- coefficient of wavelet with scale, s and time, τ (points to $\gamma(s, \tau)$)
- wavelet with scale, s , and shift, τ (points to $\Psi_{s,\tau}(t)$)

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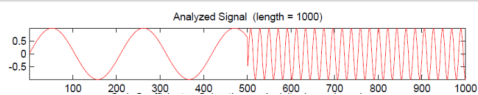
Transform Comparison



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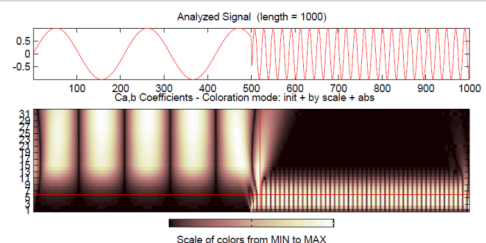
Wave Demo



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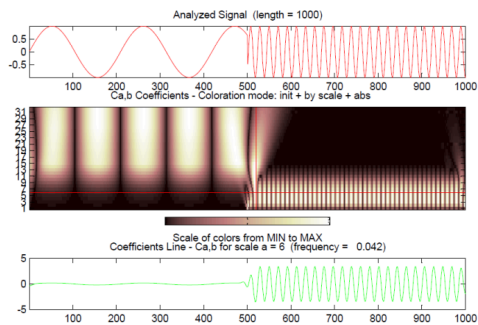
Wave Demo



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Wave Demo



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Inverse Wavelet Transform

- Build up a time-series as sum of wavelets of different scales, s , and positions, t

$$f(t) = \iint \gamma(s, \tau) \psi_{s, \tau}(t) d\tau ds$$

time-series
coefficients of wavelets
wavelet with scale, s and time, τ

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Discrete wavelets:

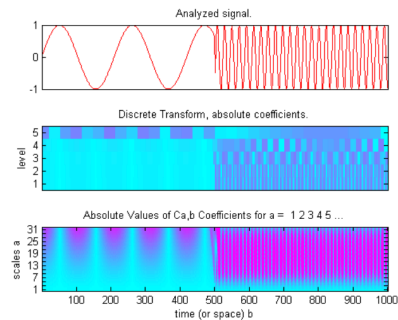
- Scale wavelets only by integer powers of 2
 - $s_j = 2^j$
- And shifting by integer multiples of s_j for each successive scale
 - $\tau_{j,k} = k2^j$
- Then $\gamma(s_j, \tau_{j,k}) = Y_{j,k}$
 - where $j = 1, 2, \dots, \infty$, $k = -\infty, \dots, -2, -1, 0, 1, 2, \dots, \infty$

$$\gamma_{j,k} = \frac{1}{\sqrt{2^j}} \int f(t) \psi\left(\frac{t - k2^j}{2^j}\right) dt$$

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DWT vs CWT



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Wavelet Transform

- Determining the wavelet coefficients for a fixed scale, s , can be thought of as a filtering operation

$$\gamma(s, \tau) = \int f(t) \Psi_{s, \tau}(t) dt$$

$$\gamma_s(t) = \int f(t) \Psi_s(t) dt = f(t) * \Psi_s(t)$$

- where

$$\Psi_s(t) = \frac{1}{\sqrt{s}} \Psi\left(\frac{t}{s}\right)$$

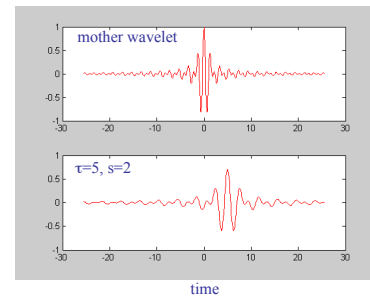
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Shannon Wavelet

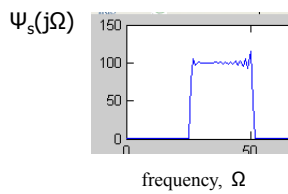
$$\Psi_{s, \tau}(t) = \frac{1}{\sqrt{s}} \Psi\left(\frac{t - \tau}{s}\right)$$

- $\Psi(t) = 2 \text{sinc}(2t) - \text{sinc}(t)$



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Fourier spectrum of Shannon Wavelet



- Wavelet coefficients are a result of bandpass filtering

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Discrete Wavelet Transform

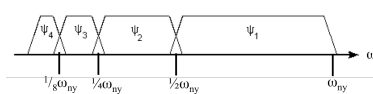
- The coefficients of Ψ is just the band-pass filtered time-series, where Ψ is the wavelet, now viewed as the impulse response of a bandpass filter.
 - Discrete wavelet $\rightarrow s = 2^j$

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Discrete Wavelet Transform

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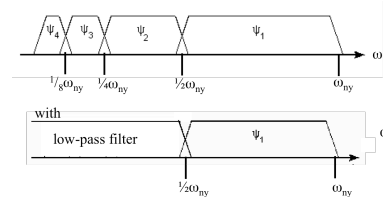


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Discrete Wavelet Transform

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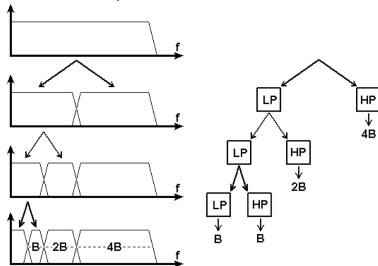


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Digital Wavelet as Multirate Filter Bank

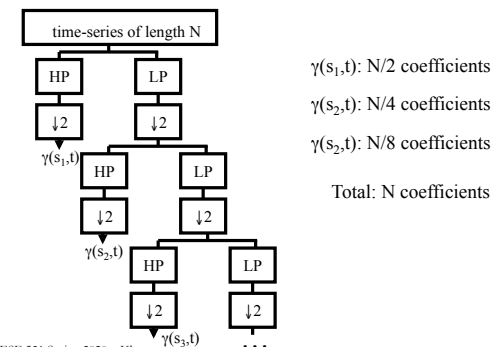
- Repeat recursively!



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Digital Wavelet as Multirate Filter Bank

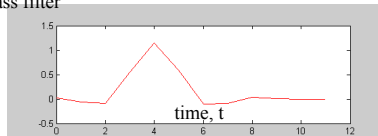


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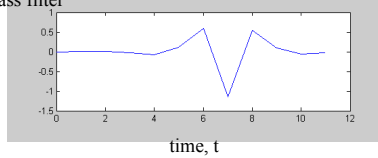
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Impulse Responses

Coiflet low pass filter



Coiflet high-pass filter

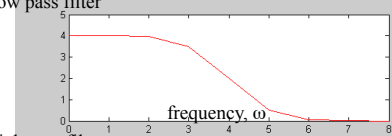


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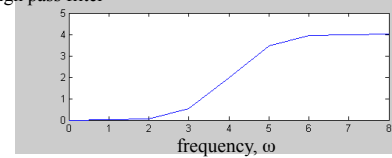
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Filter Responses

Spectrum of low pass filter

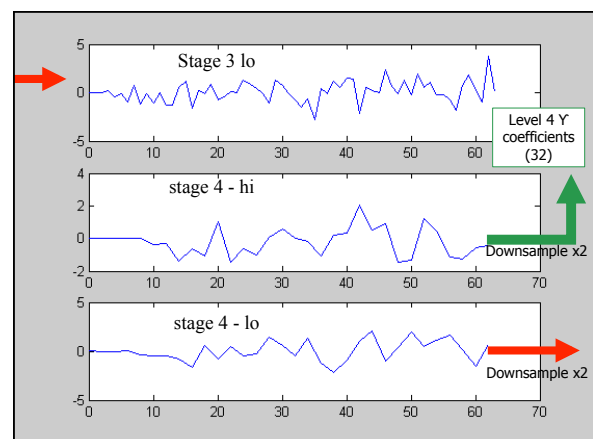
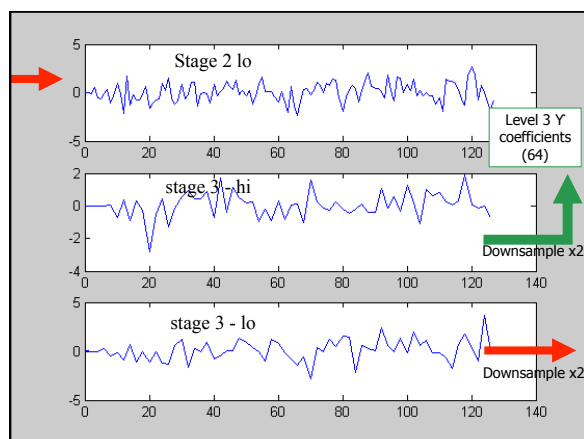
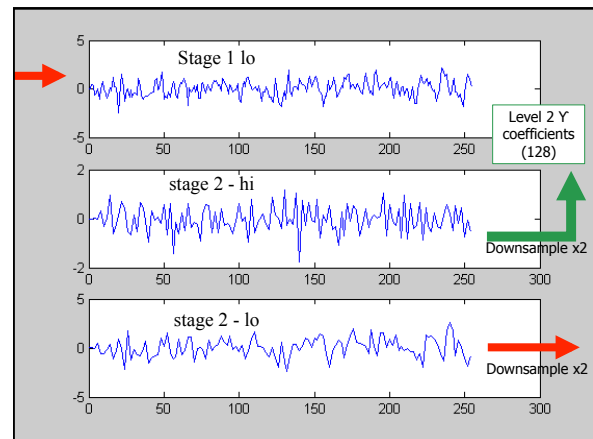
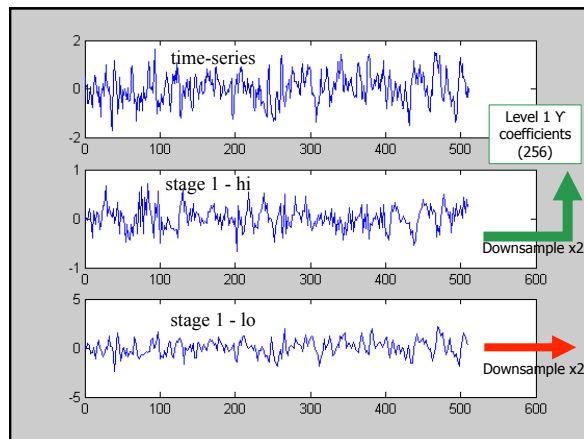


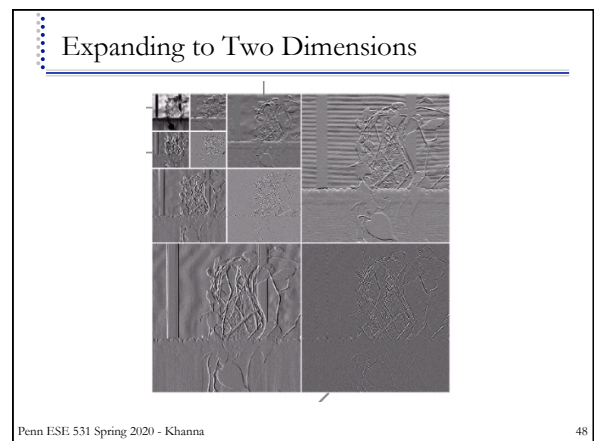
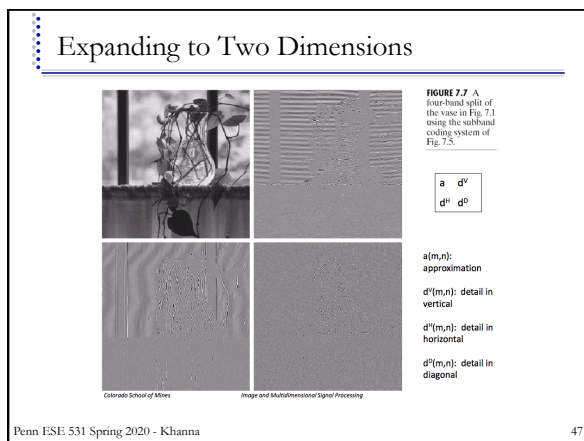
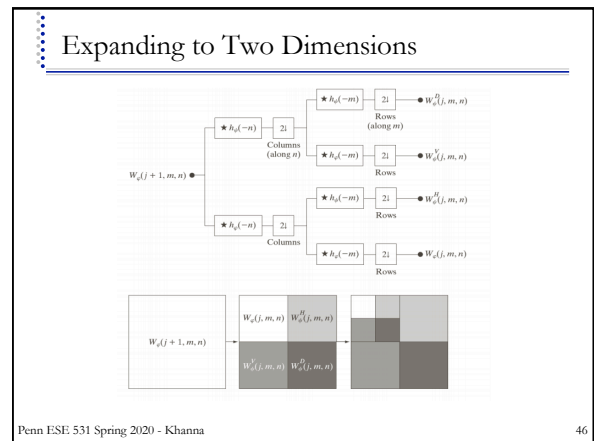
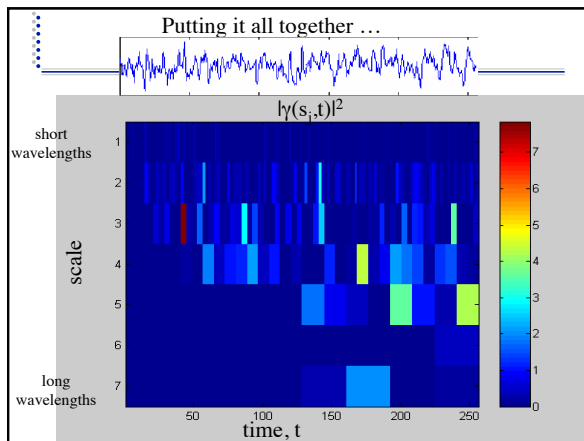
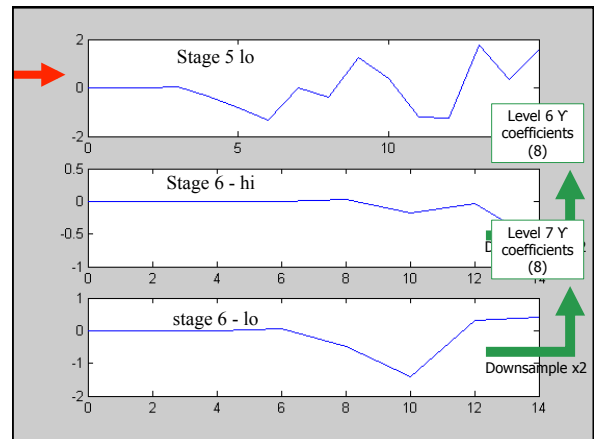
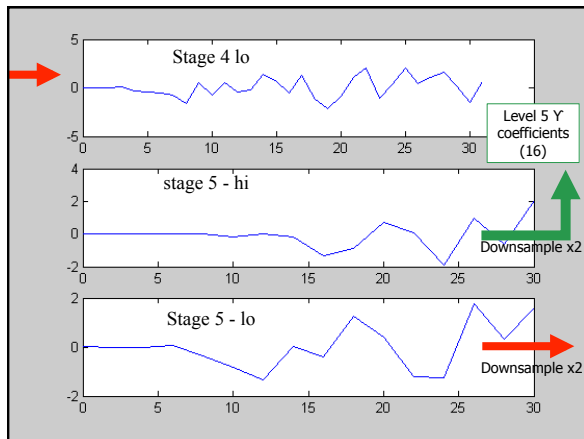
Spectrum of high pass filter



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Big Ideas

- Wavelet transform
 - Capture temporal data with fewer coefficients than STFT
 - Use scaling and translation to get different resolution at different levels

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Admin

- Project
 - Due 4/28
- Final Exam – 5/7 (3pm-5pm)
 - In Canvas
 - Will have a 2 hr window to complete within a 12 hr window
 - Open course notes and textbook, but cannot communicate with each other about the exam
 - Students will have randomized and different questions
 - Reminder, it is not in your best interest to share the exam
 - Old exams posted on old course websites
 - Covers Lec 1- 20
 - Does not include lec 12 (data converters and noise shaping) or IIR Filters

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