ESE 531: Digital Signal Processing

Week 15

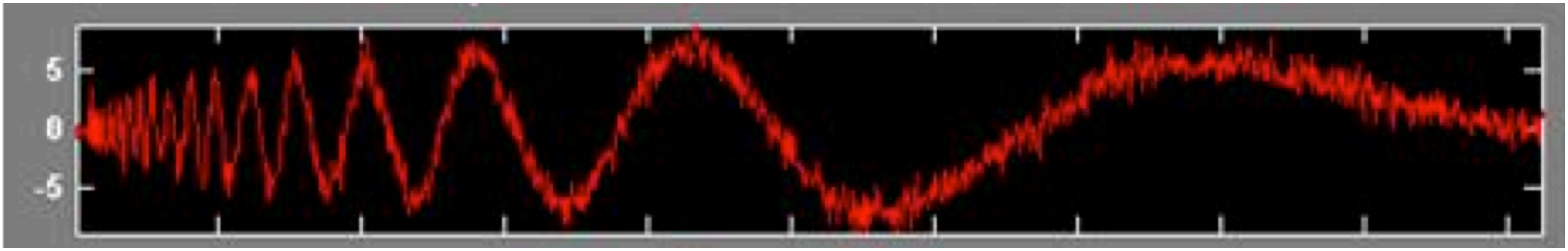
Lecture 27: April 25, 2021

Wavelet Transform

Wavelet Transform

Motivation

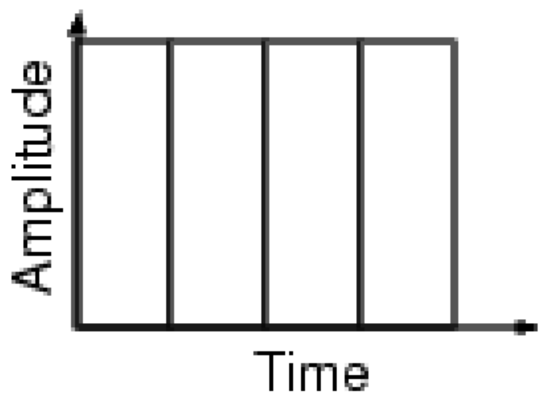
- Some signals obviously have spectral characteristics that vary with time



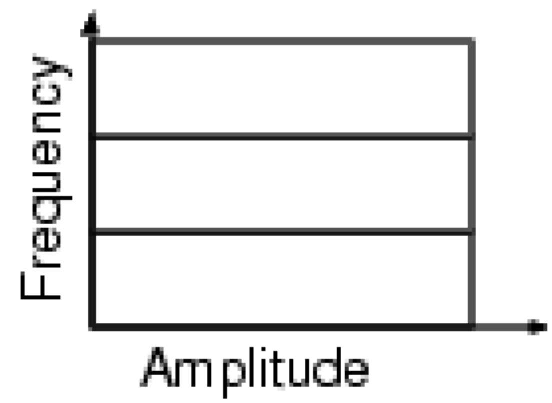
Criticism of Fourier Spectrum

- It's giving you the spectrum of the 'whole time-series'
- Which is OK if the time-series is stationary. But what if its 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

Transform Comparison

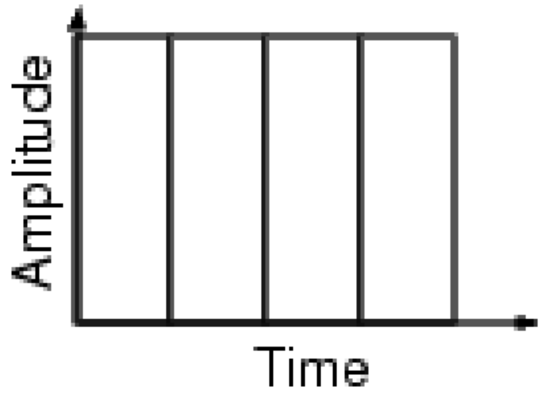


Time Domain (Shannon)

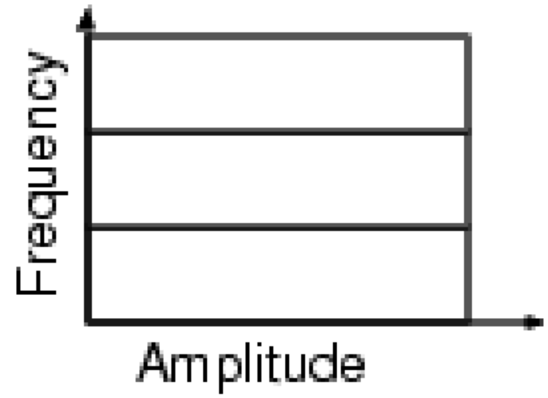


Frequency Domain (Fourier)

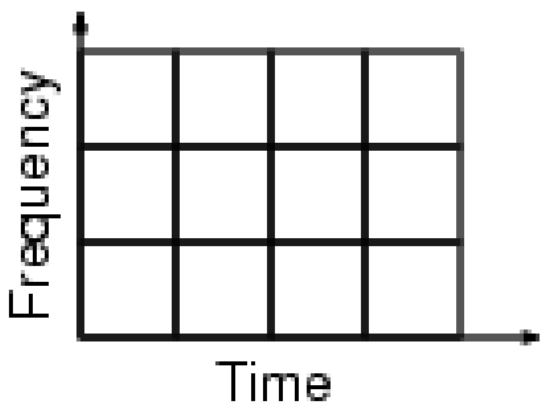
Transform Comparison



Time Domain (Shannon)



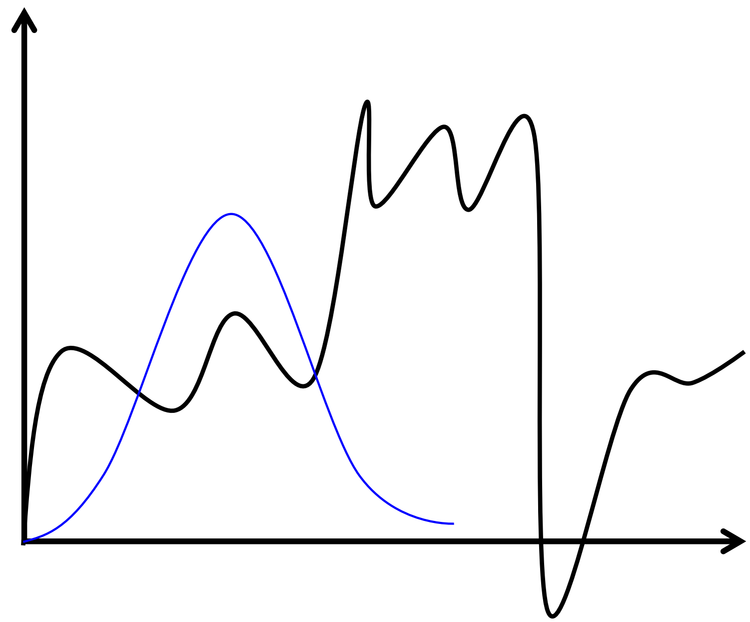
Frequency Domain (Fourier)



STFT (Gabor)

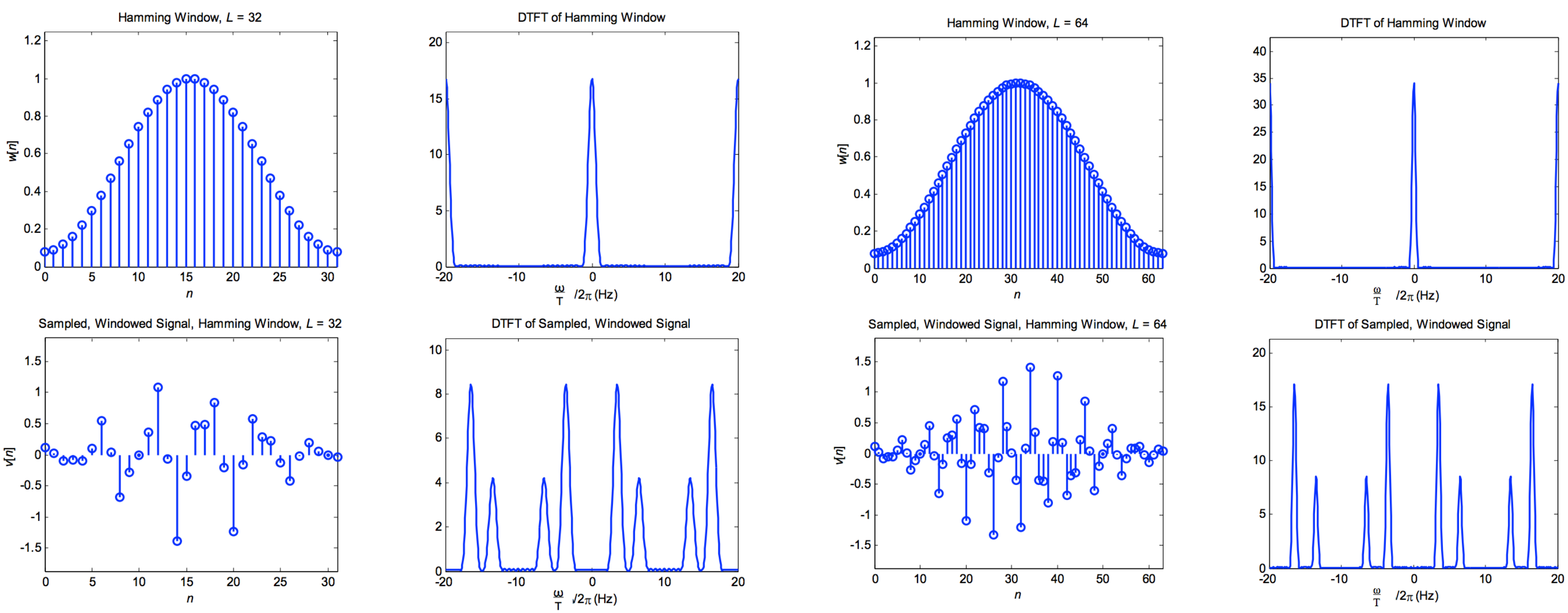
Discrete Time-Dependent FT

- Fixed window size, shift in time (Gabor)

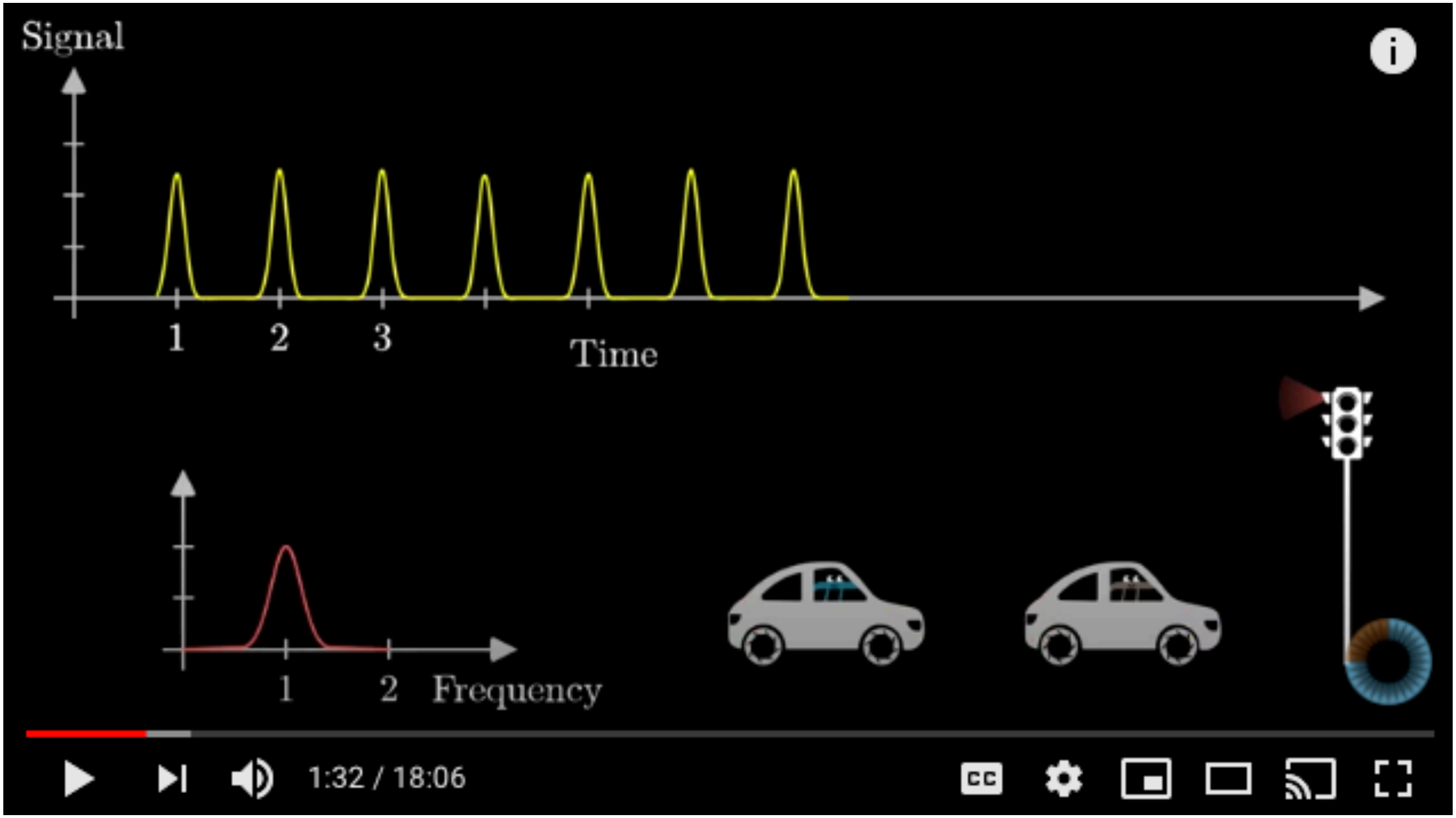


Windowed Sampled CT Signal Example

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



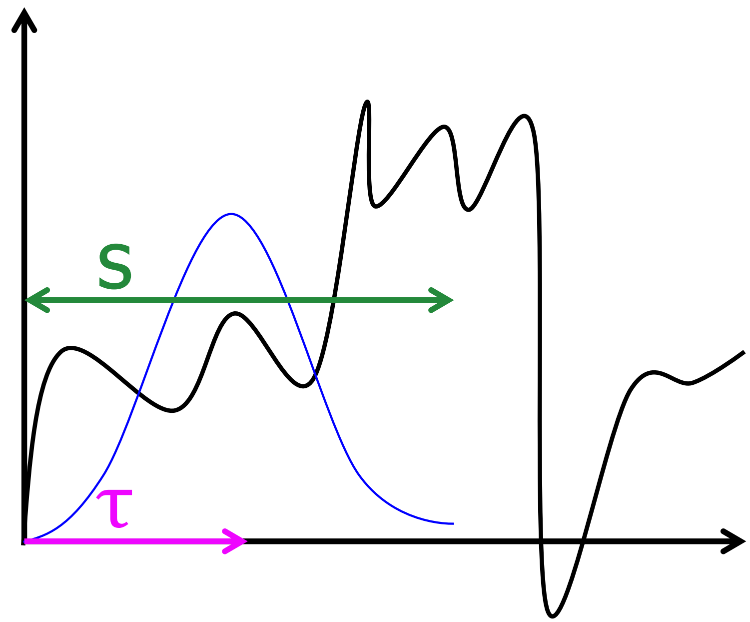
Uncertainty Principle



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

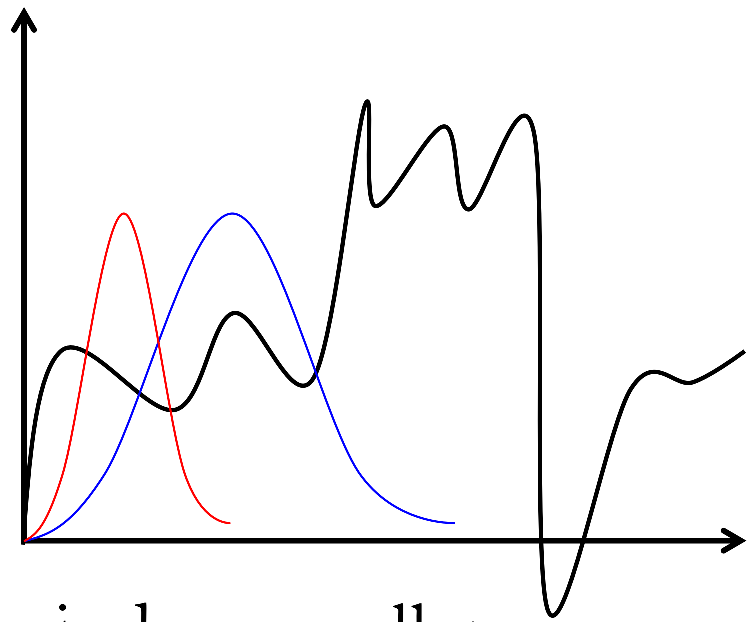
Discrete Time-Dependent FT

- Fixed window size, shift in time (Gabor)



Discrete Time-Dependent FT

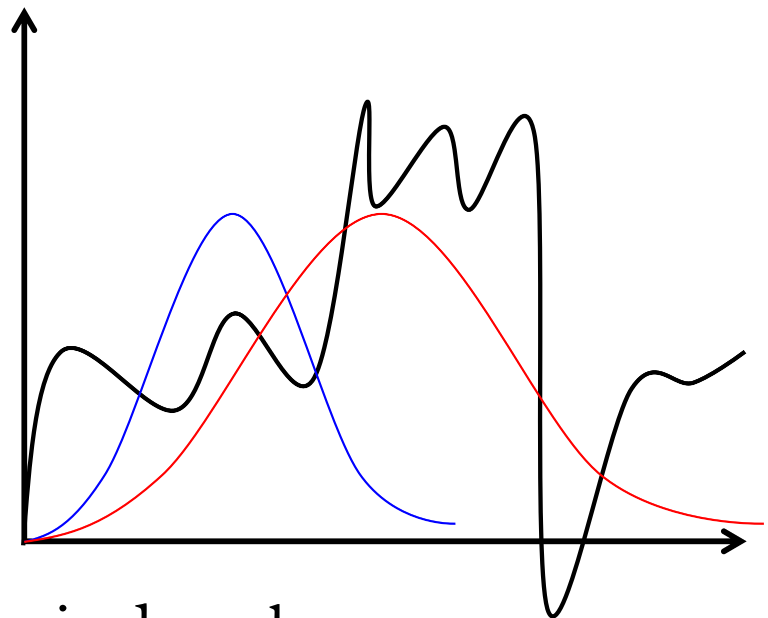
- Fixed window size, shift in time (Gabor)



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

Discrete Time-Dependent FT

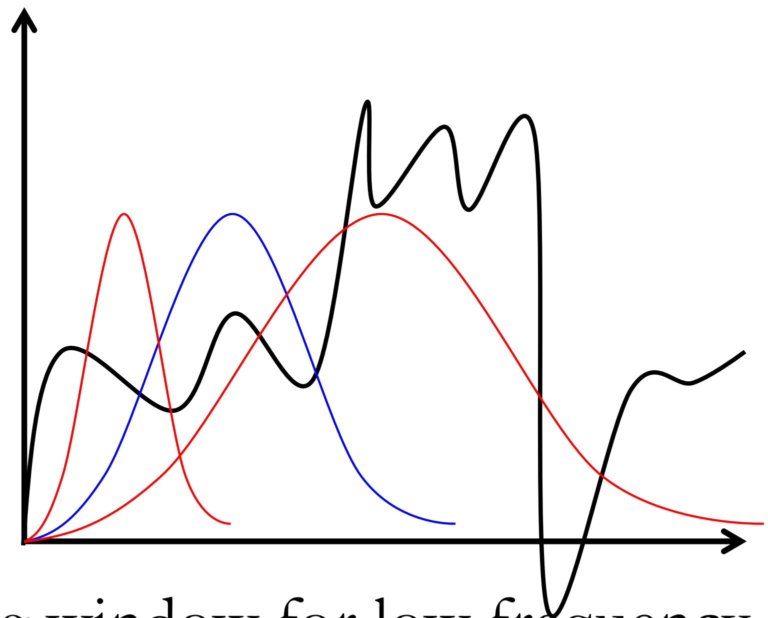
- Fixed window size, shift in time (Gabor)



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

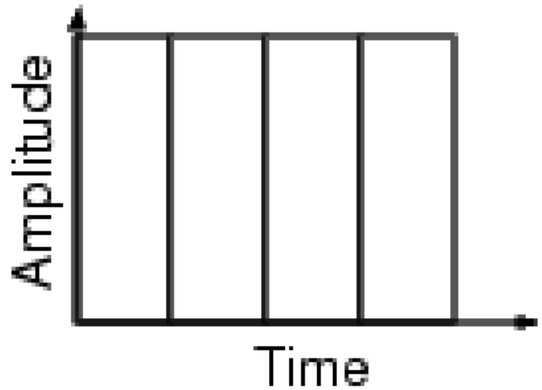
Discrete Time-Dependent FT

- Fixed window size, shift in time (Gabor)

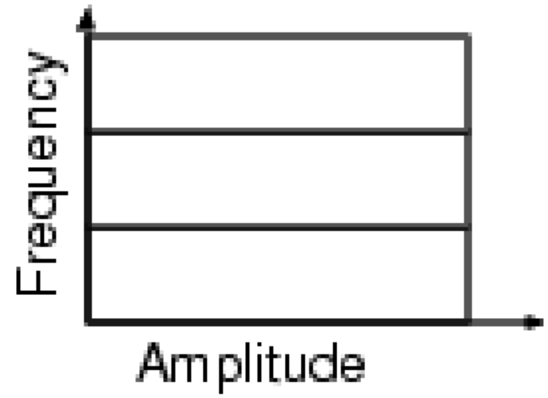


  - Use a big window for low frequency content that is not localized in time
  - Use a small window for high frequency content that is localized in time

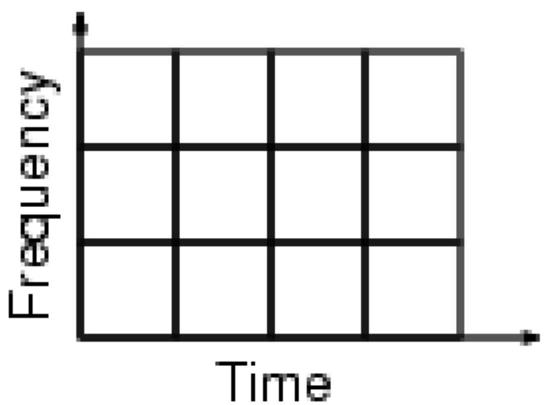
Transform Comparison



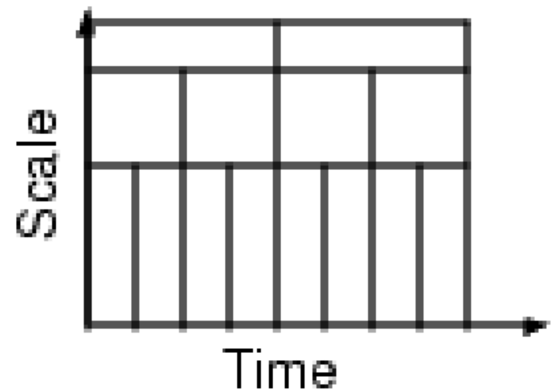
Time Domain (Shannon)



Frequency Domain (Fourier)



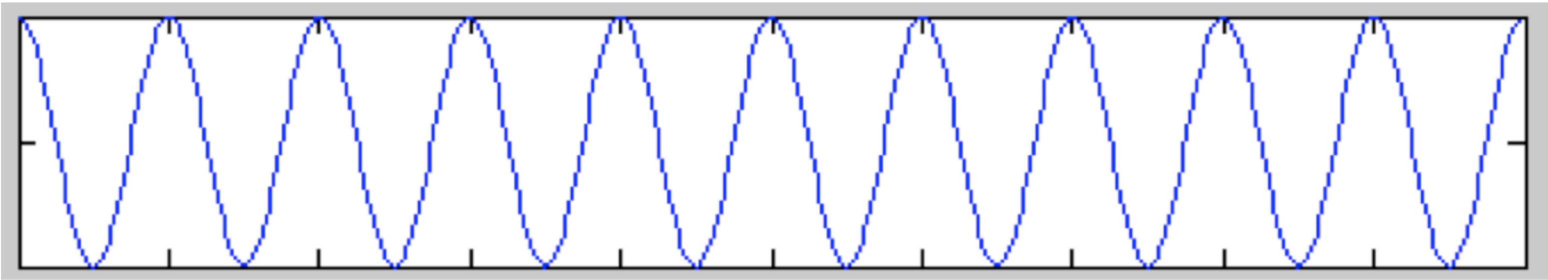
STFT (Gabor)



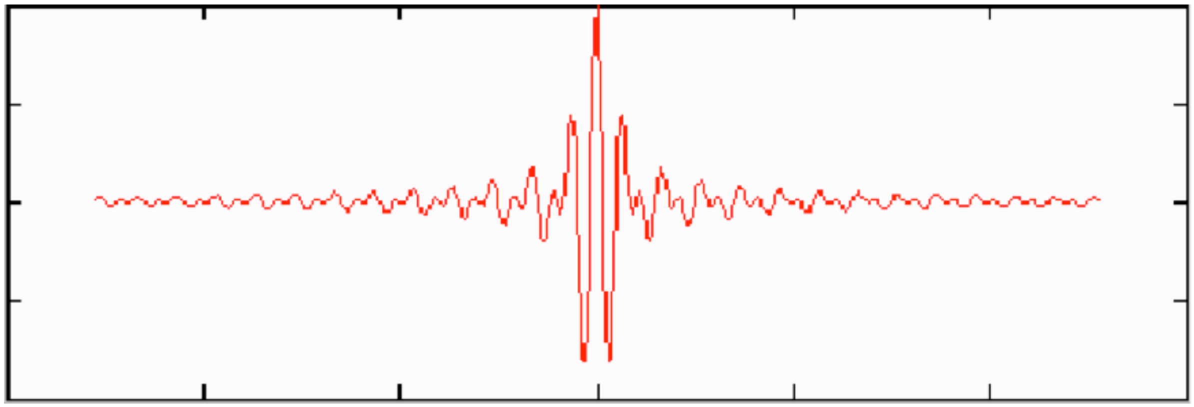
Wavelet Analysis

Fourier vs. Wavelet

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



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

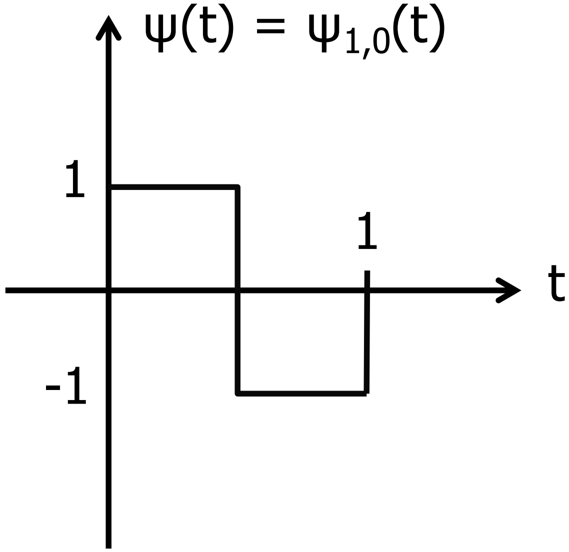


Wavelet Transform

- All wavelets derived from *mother* wavelet

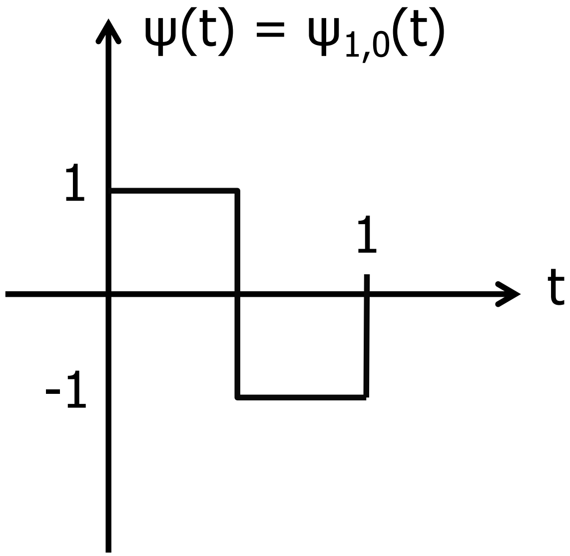
$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right)$$

Example: Haar Wavelet



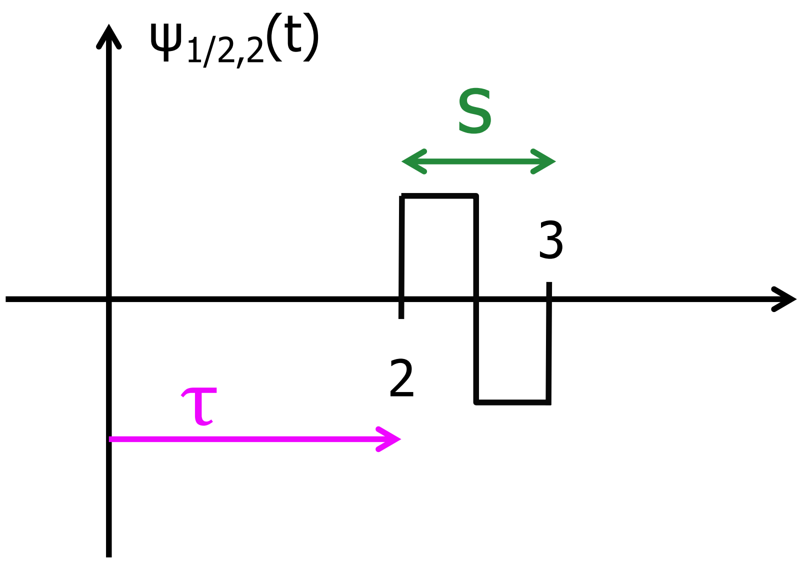
$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right)$$

Example: Haar Wavelet

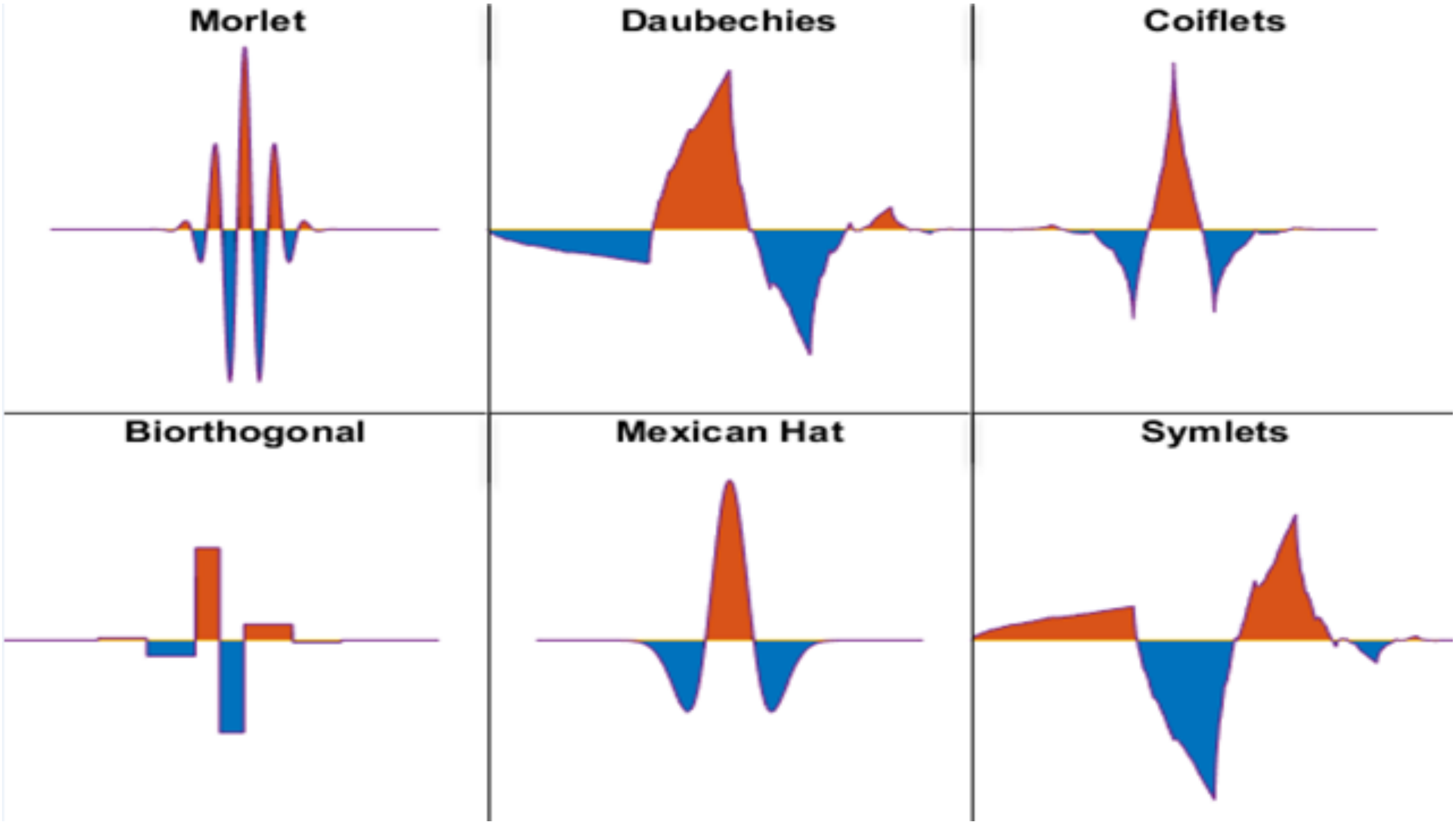


$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right)$$

s=1/2, τ=2



Examples of Wavelets



Wavelet – Scaled and Shifted

normalization

shift in time

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

change in scale

wavelet with
scale, s and
translation, τ

Mother wavelet

Continuous Wavelet Transform

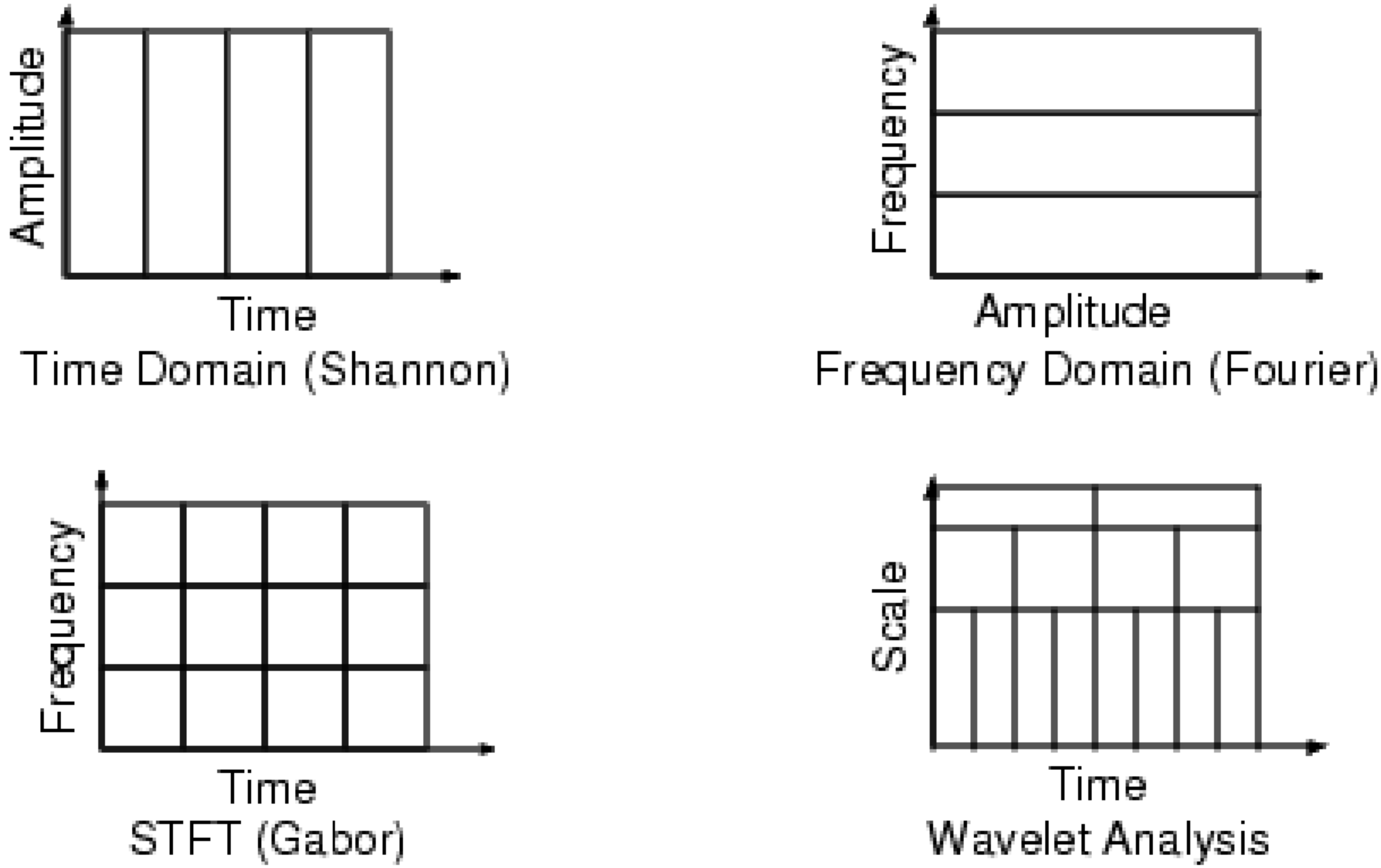
time-series

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

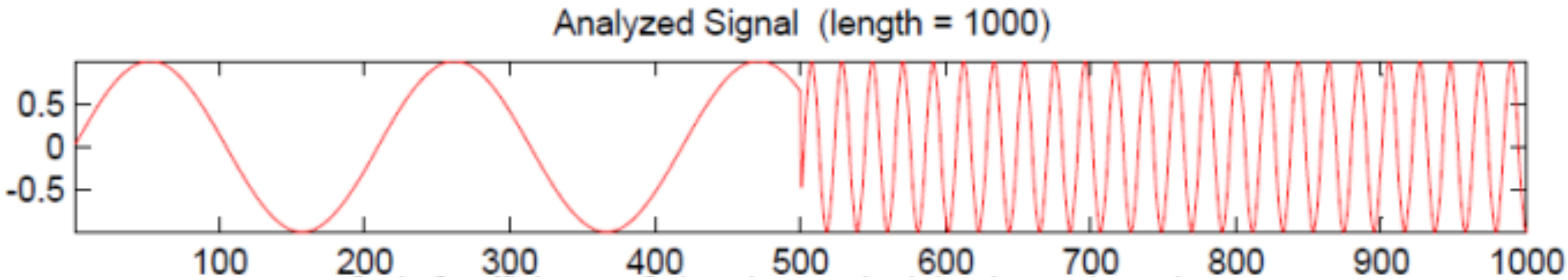
coefficient of wavelet with scale, s and time, τ

wavelet with scale, s, and shift, τ

Transform Comparison

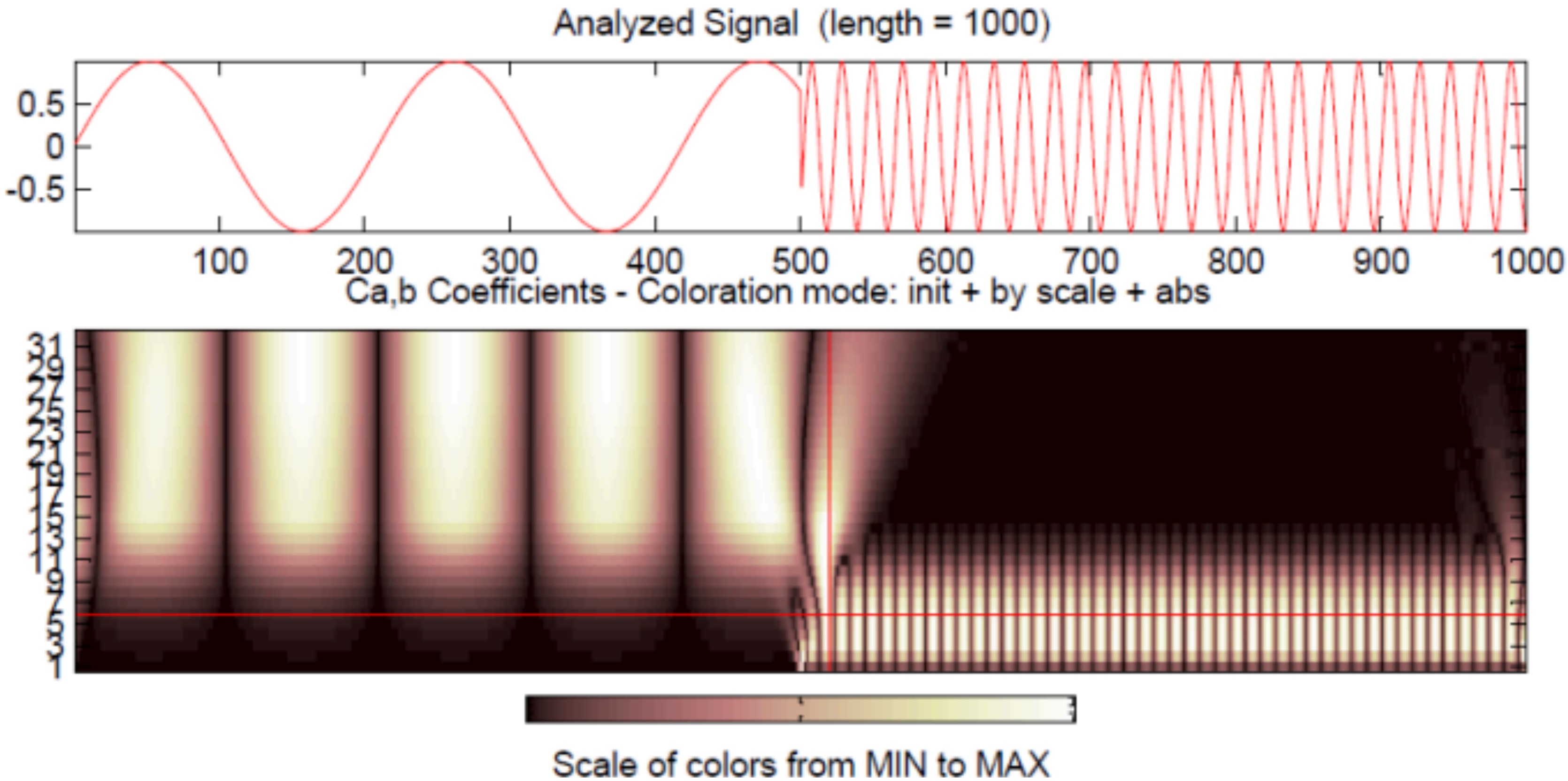


Wave Demo



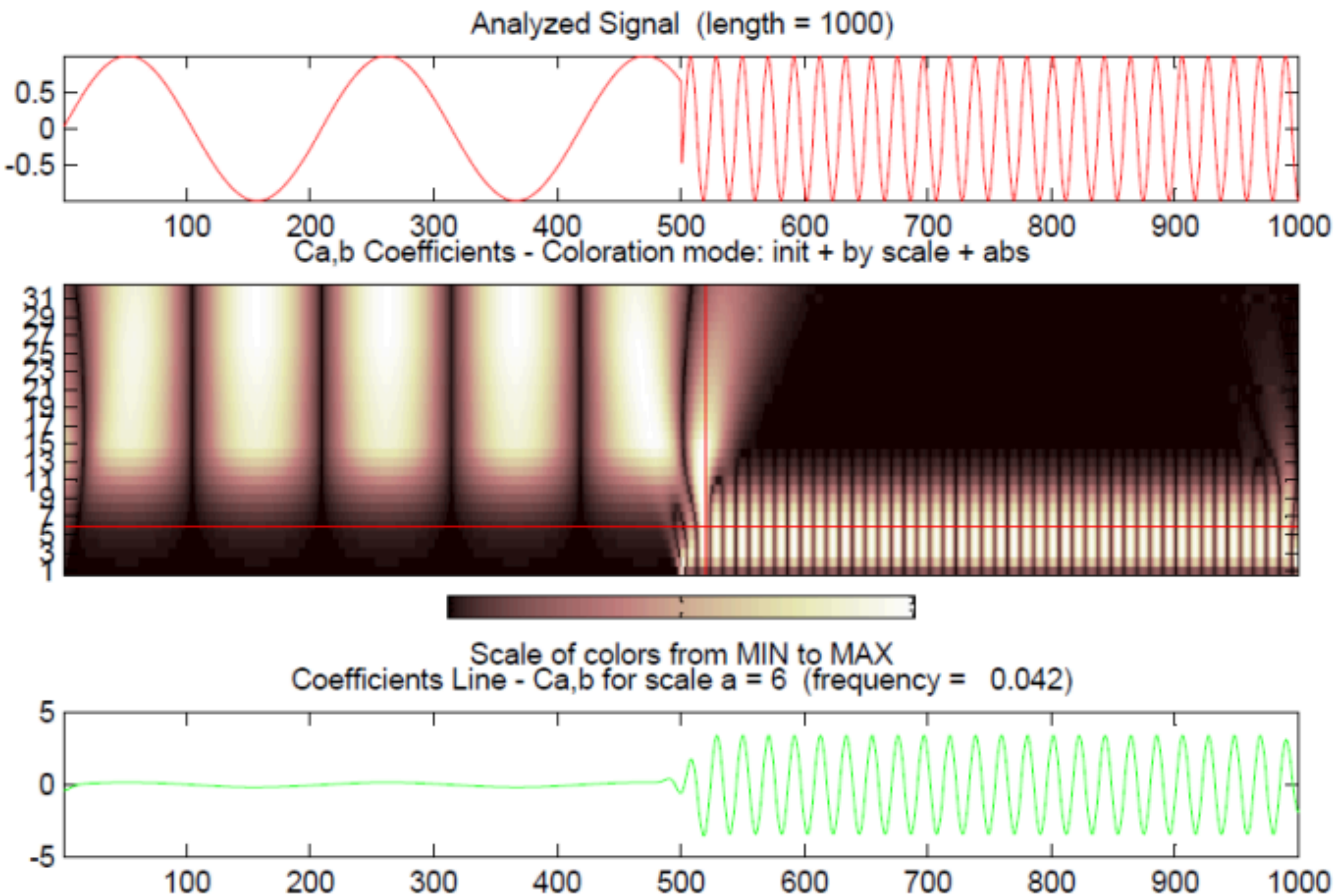
Analyzed Signal (length = 1000)
0.5
0
-0.5
100
200
300
400
500
600
700
800
900
1000

Wave Demo



Analyzed Signal (length = 1000)
0.5
0
-0.5
100
200
300
400
500
600
700
800
900
1000
Ca,b Coefficients - Coloration mode: init + by scale + abs
Scale of colors from MIN to MAX

Wave Demo



Analyzed Signal (length = 1000)
0.5
0
-0.5
100
200
300
400
500
600
700
800
900
1000
Ca,b Coefficients - Coloration mode: init + by scale + abs
Scale of colors from MIN to MAX
Coefficients Line - Ca,b for scale a = 6 (frequency = 0.042)
5
0
-5

Inverse Wavelet Transform

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

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

time-series

coefficients of wavelets

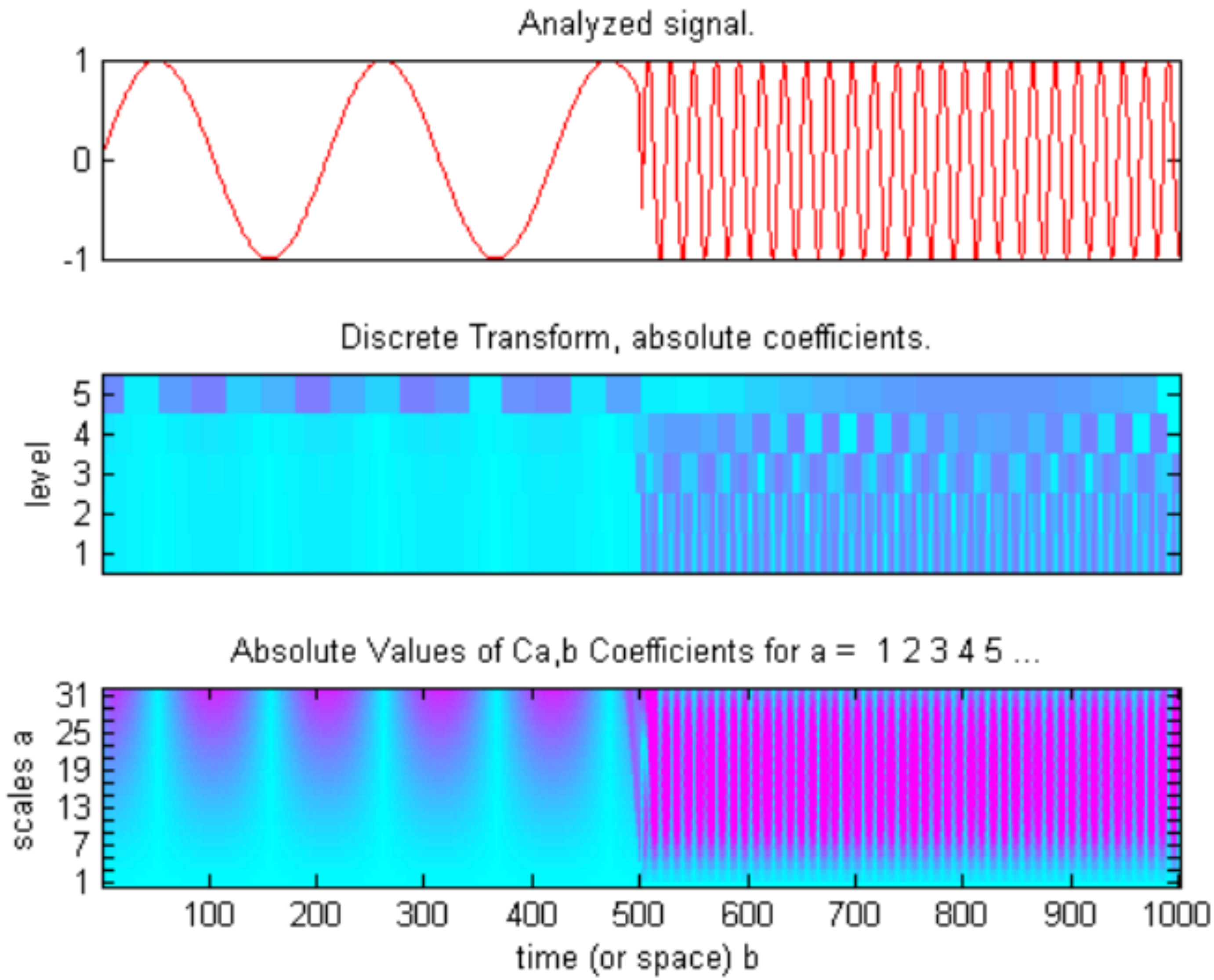
wavelet with scale, s and time, τ

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 $\gamma(s_j, \tau_{j,k}) = \gamma_{jk}$
  - where j = 1, 2, …□ , k = -□ … -2, -1, 0, 1, 2, …□

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

DWT vs CWT



Analyzed signal.
1
0
-1
Discrete Transform, absolute coefficients.
level
5
4
3
2
1
Absolute Values of Ca,b Coefficients for a = 1 2 3 4 5 ...
scales a
31
25
19
13
7
1
100
200
300
400
500
600
700
800
900
1000
time (or space) b

Wavelet Transform

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

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

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

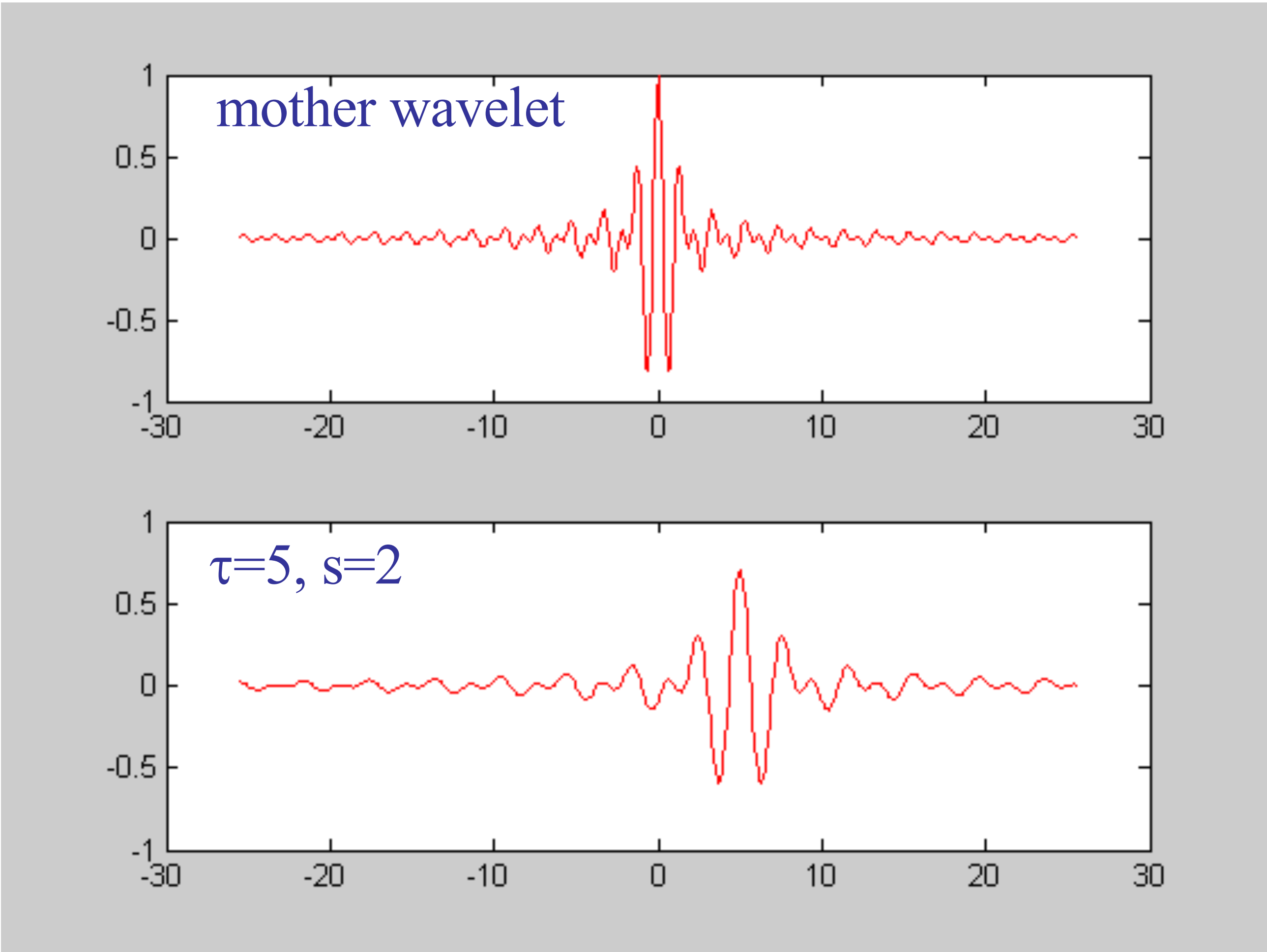
- where

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

Shannon Wavelet

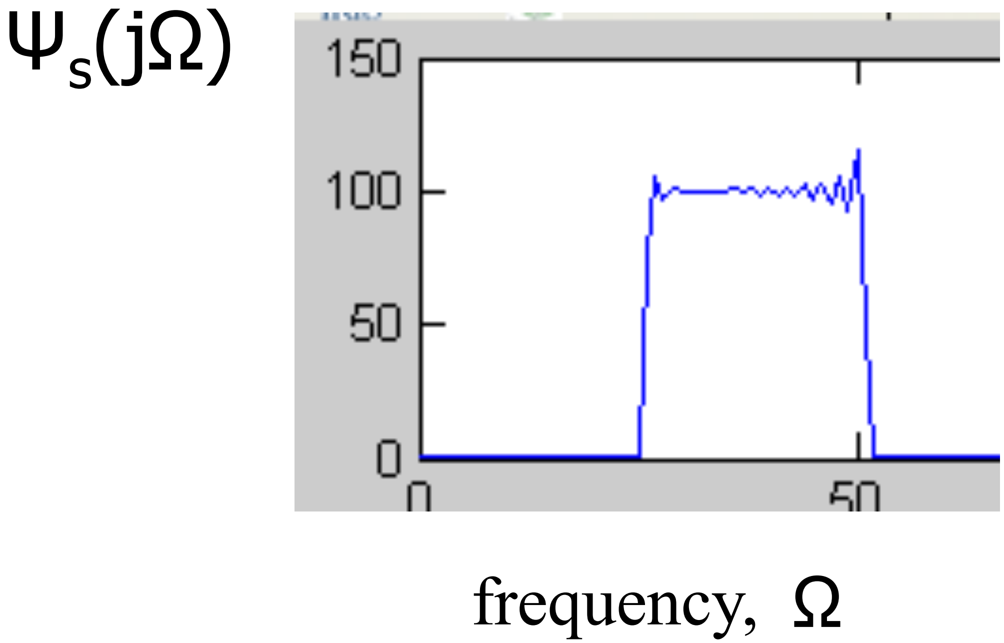
$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right)$$

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



time

Fourier spectrum of Shannon Wavelet



- Wavelet coefficients are a result of bandpass filtering

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 → $s = 2^j$

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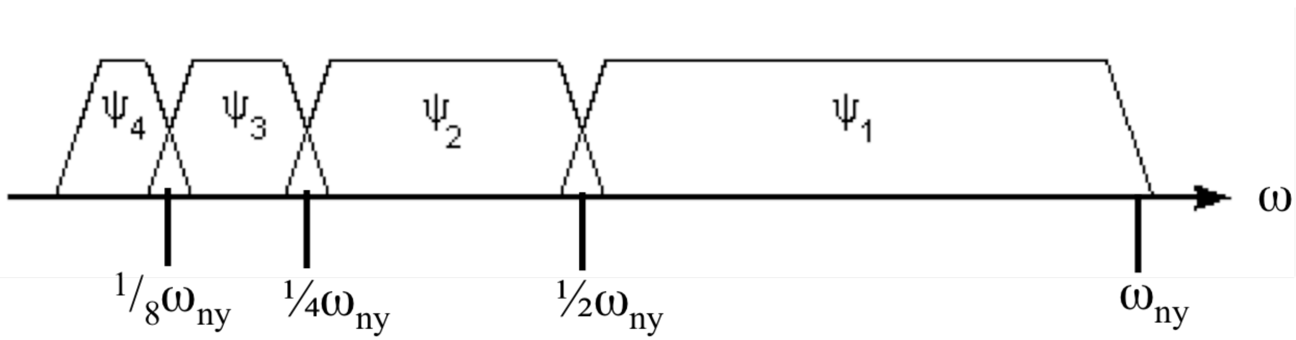

Discrete Wavelet Transform

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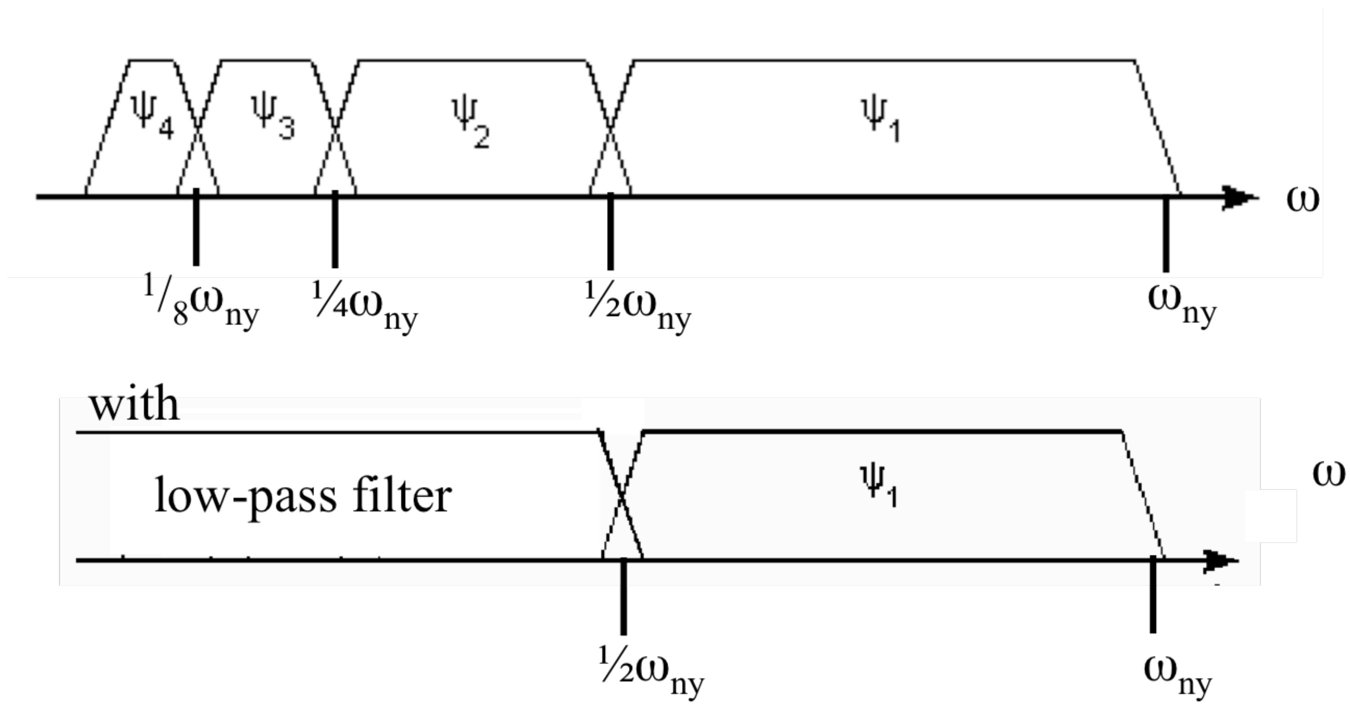
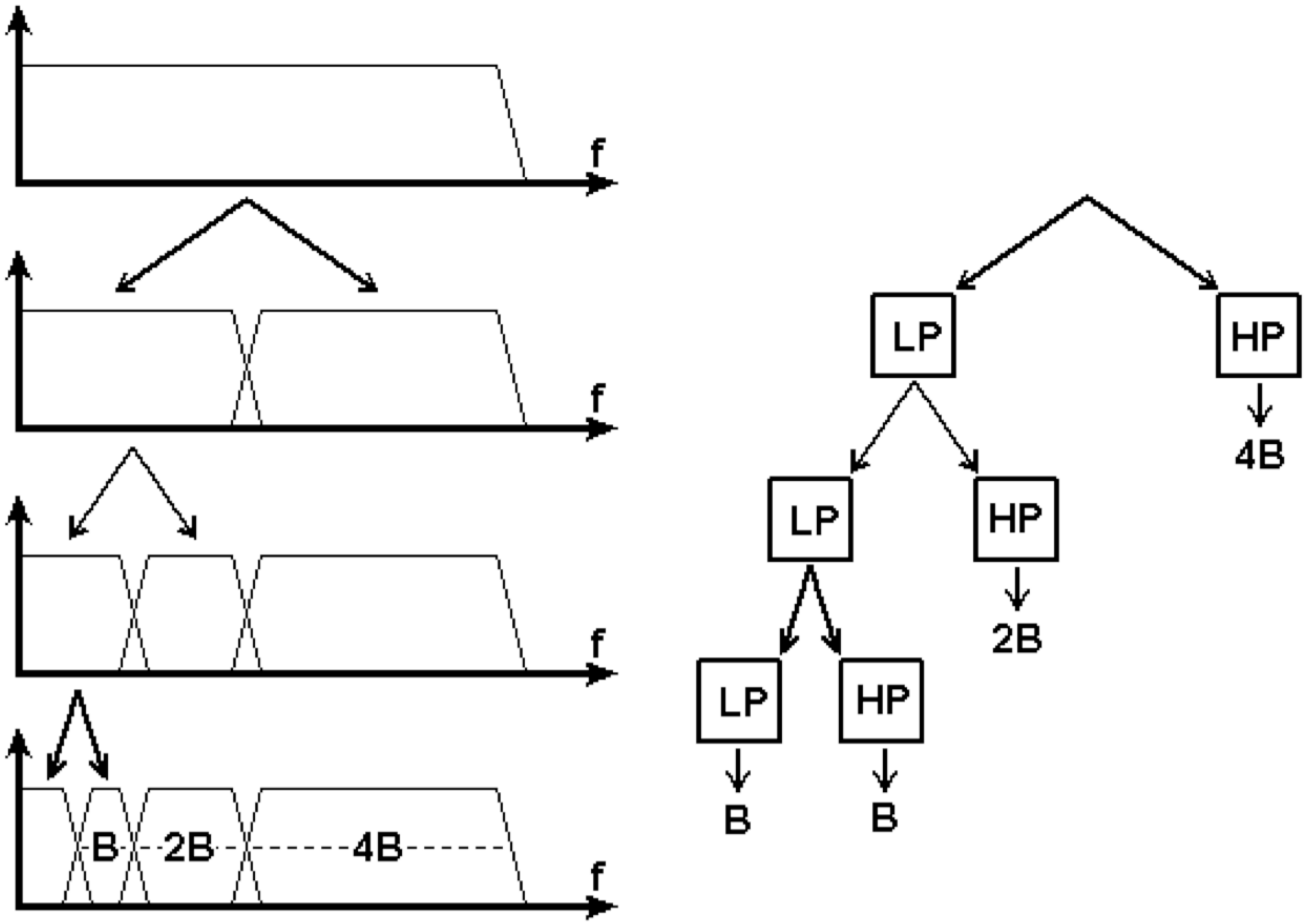
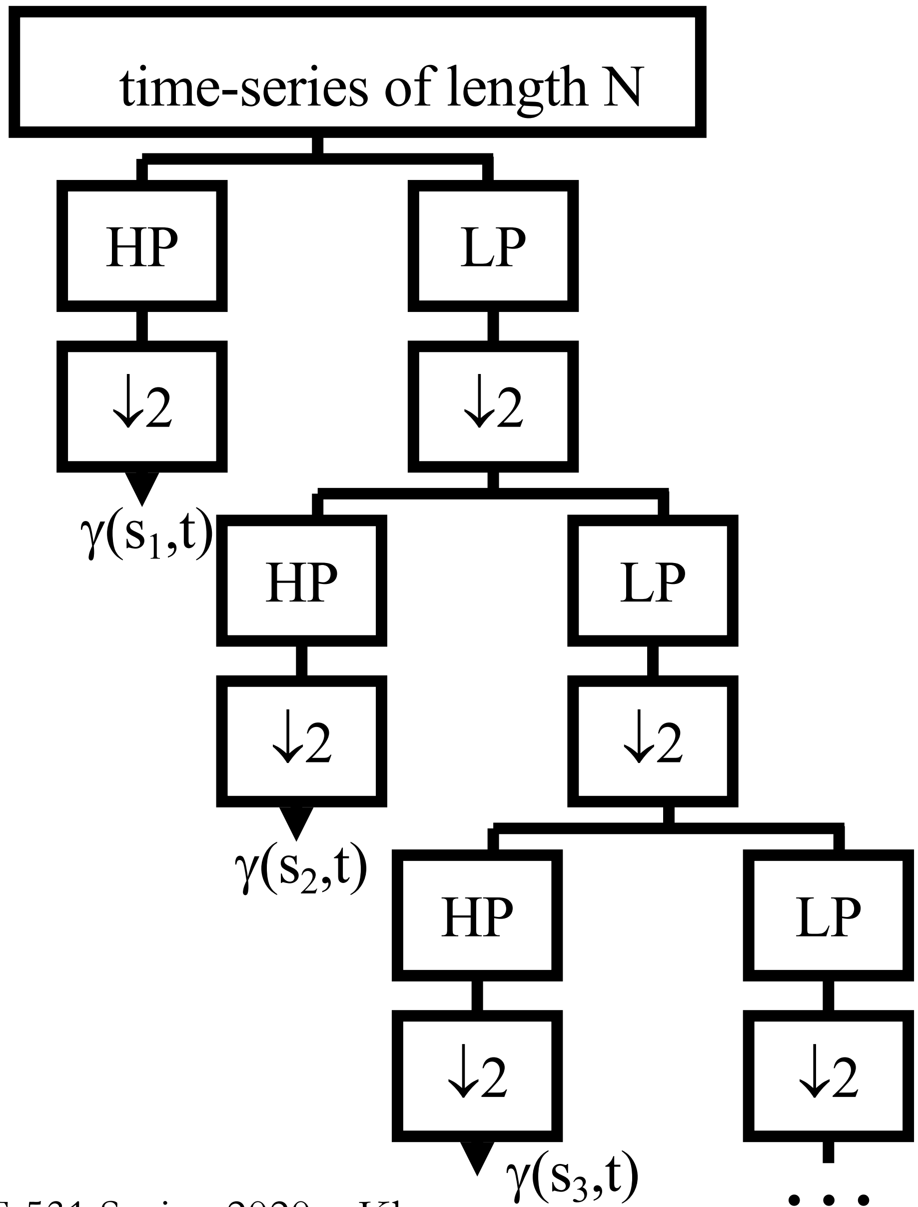


Digital Wavelet as Multirate Filter Bank

- Repeat recursively!



Digital Wavelet as Multirate Filter Bank



$\gamma(s_1,t)$: N/2 coefficients

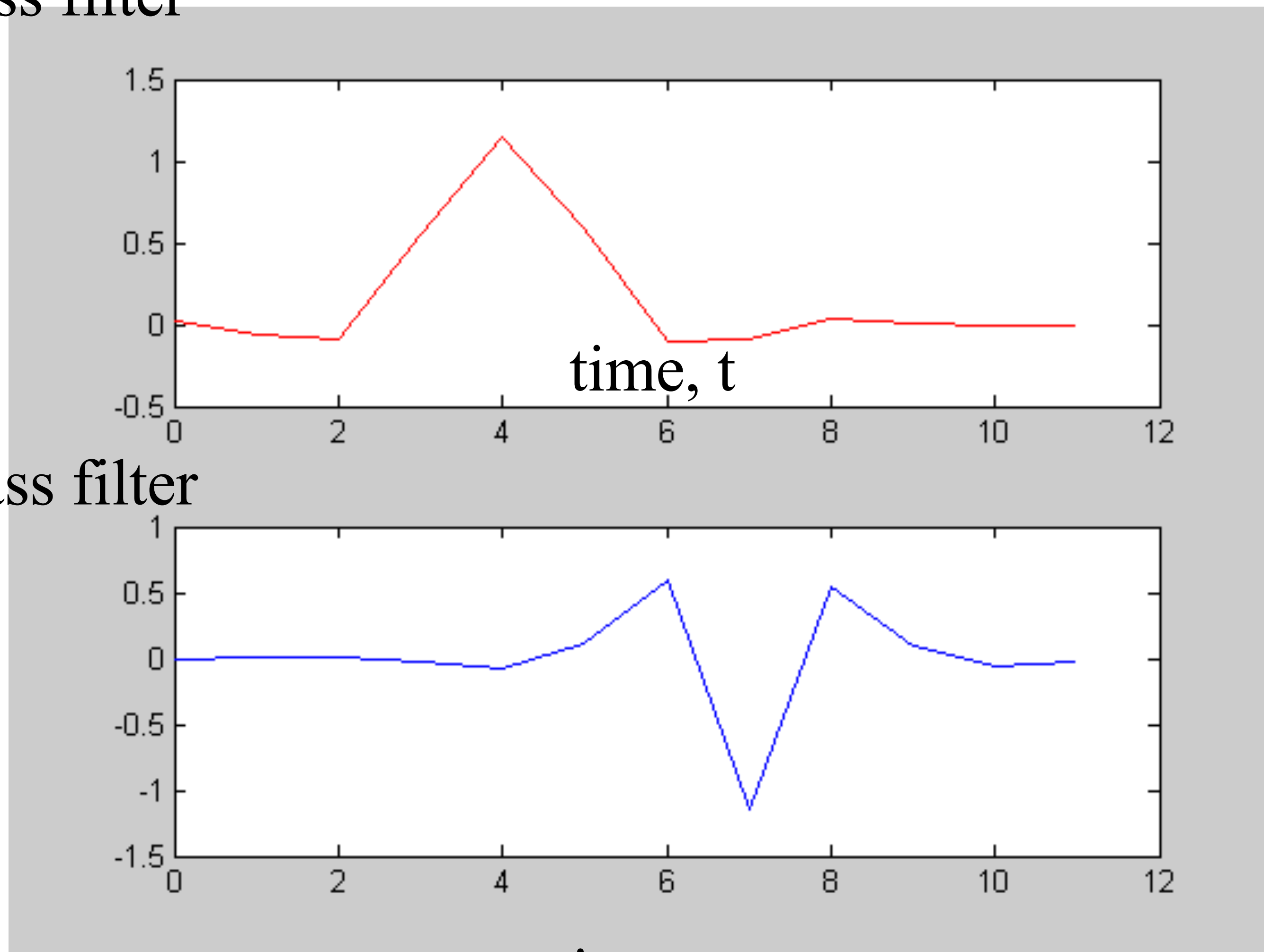
$\gamma(s_2,t)$: N/4 coefficients

$\gamma(s_2,t)$: N/8 coefficients

Total: N coefficients

Impulse Responses

Coiflet low pass filter



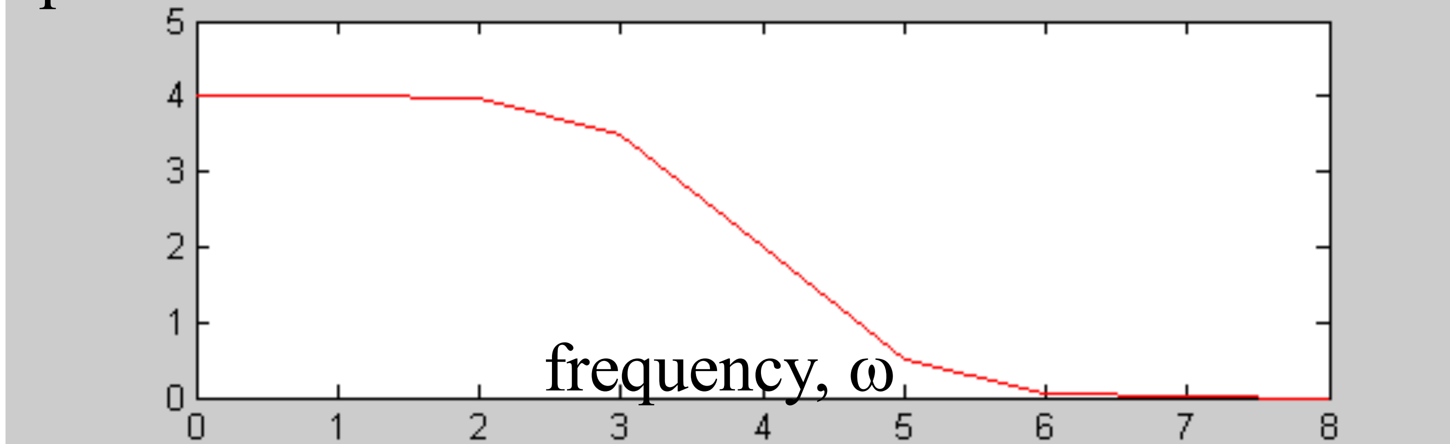
time, t

Coiflet high-pass filter

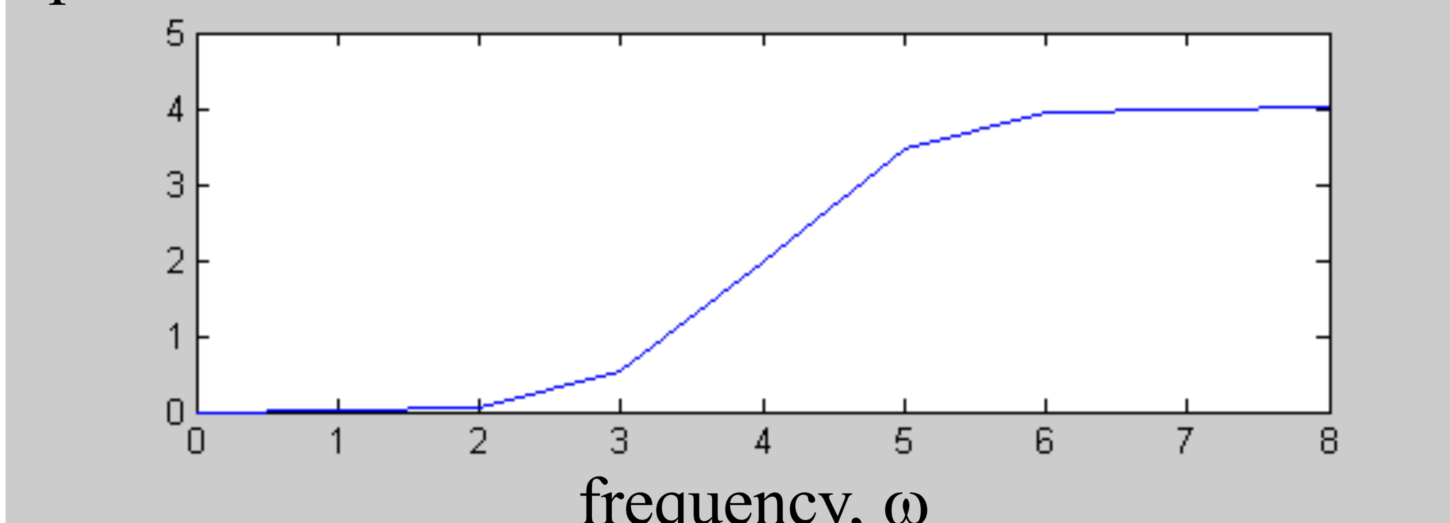
time, t

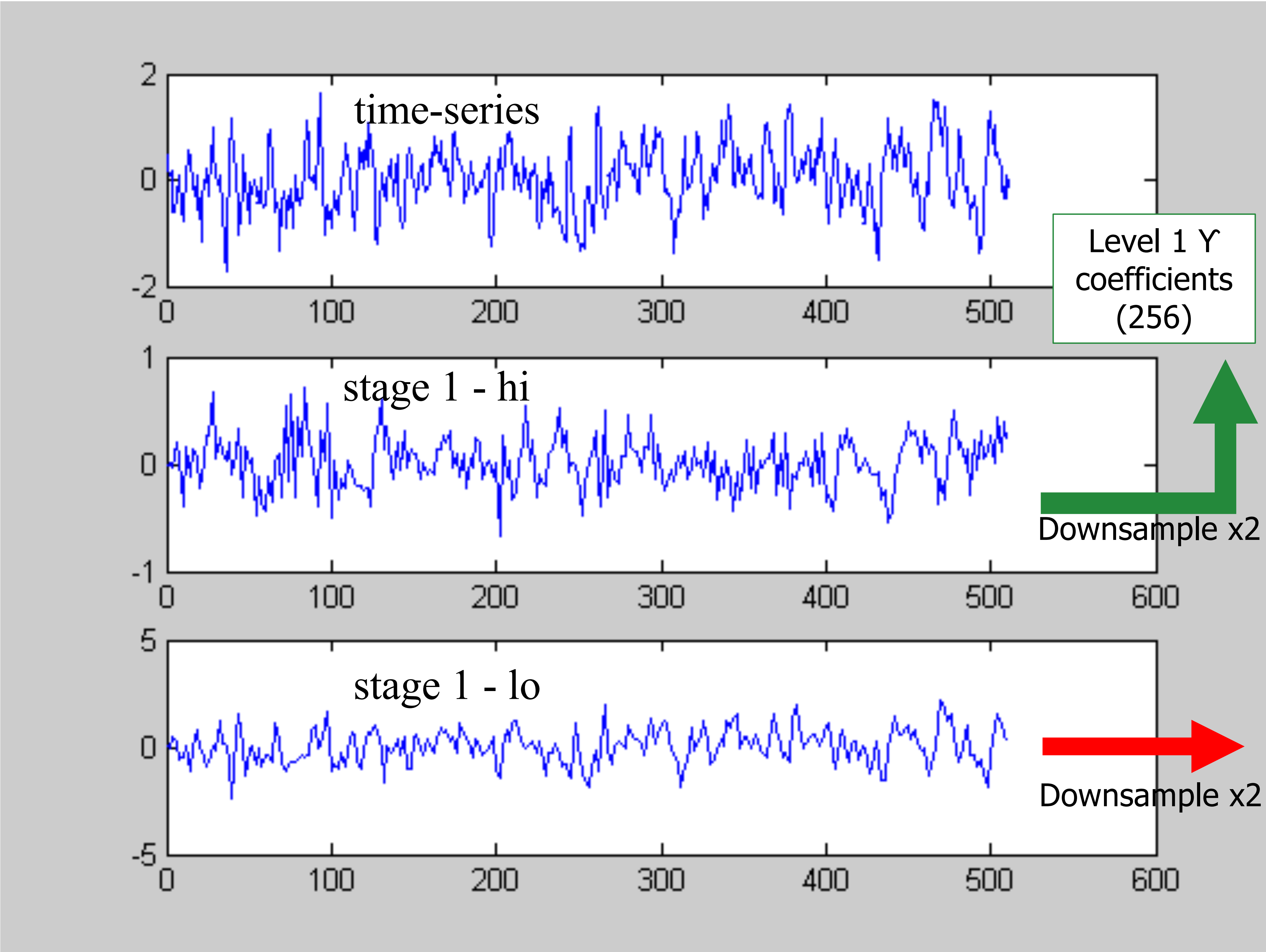
Filter Responses

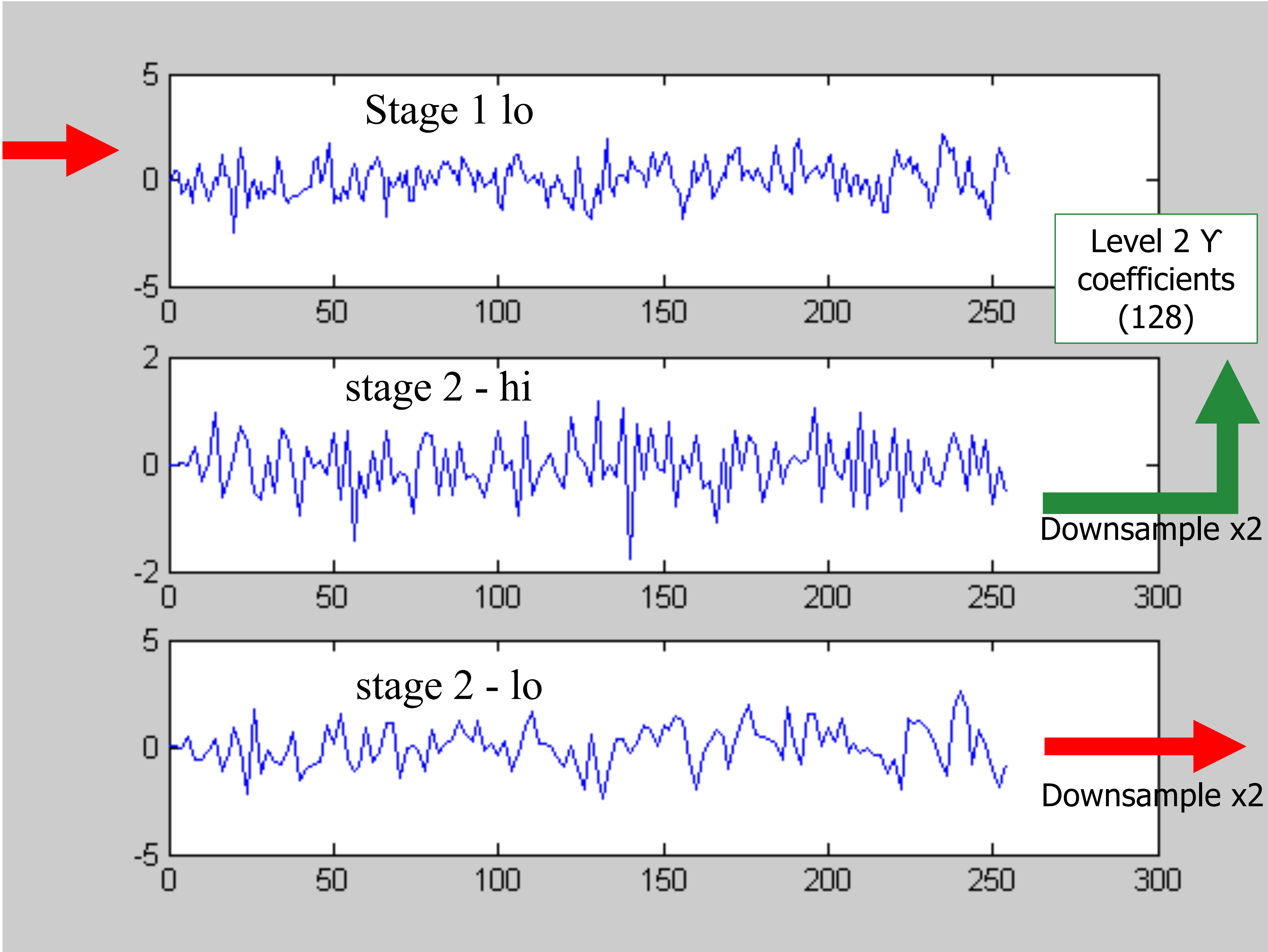
Spectrum of low pass filter

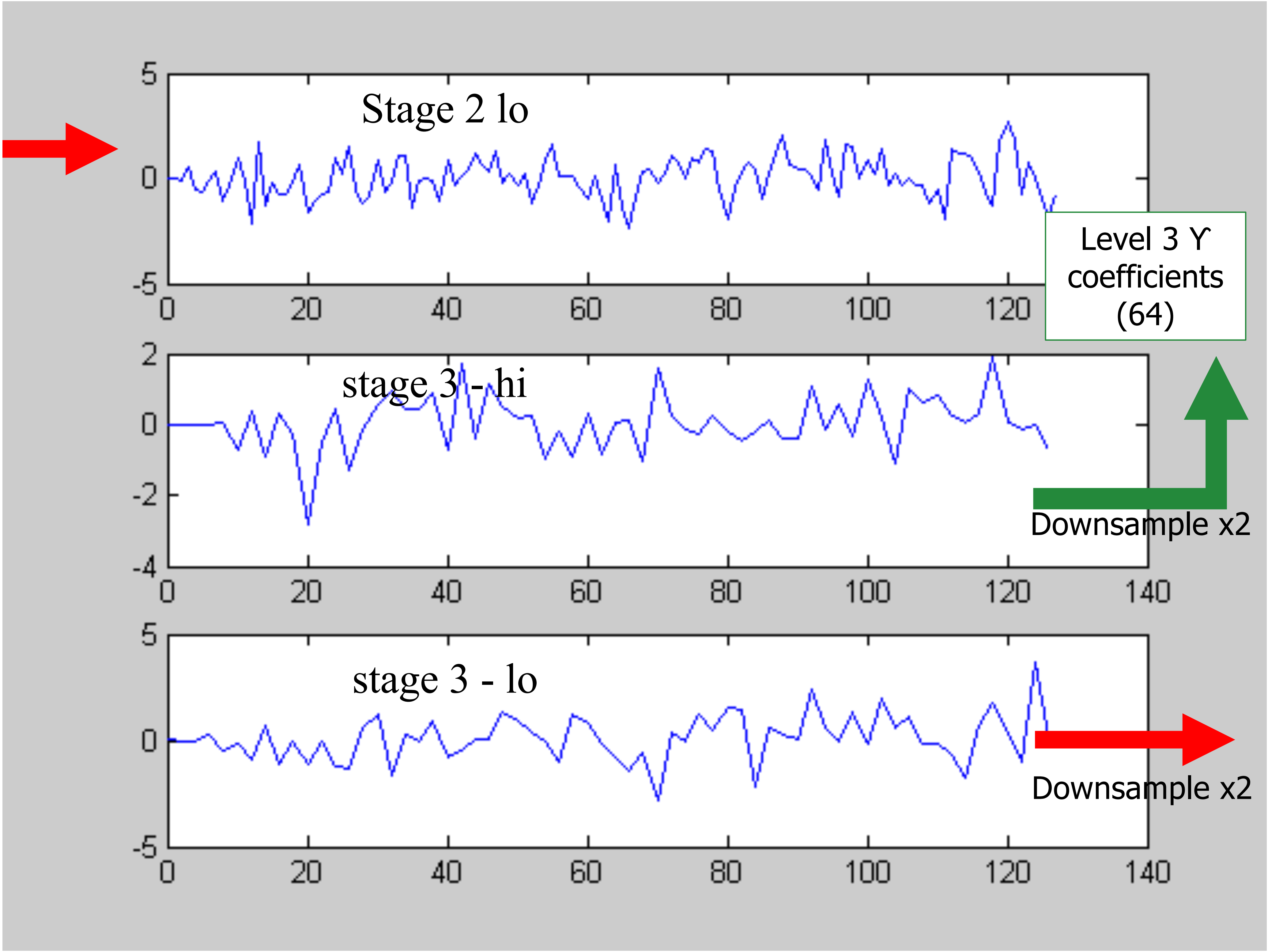


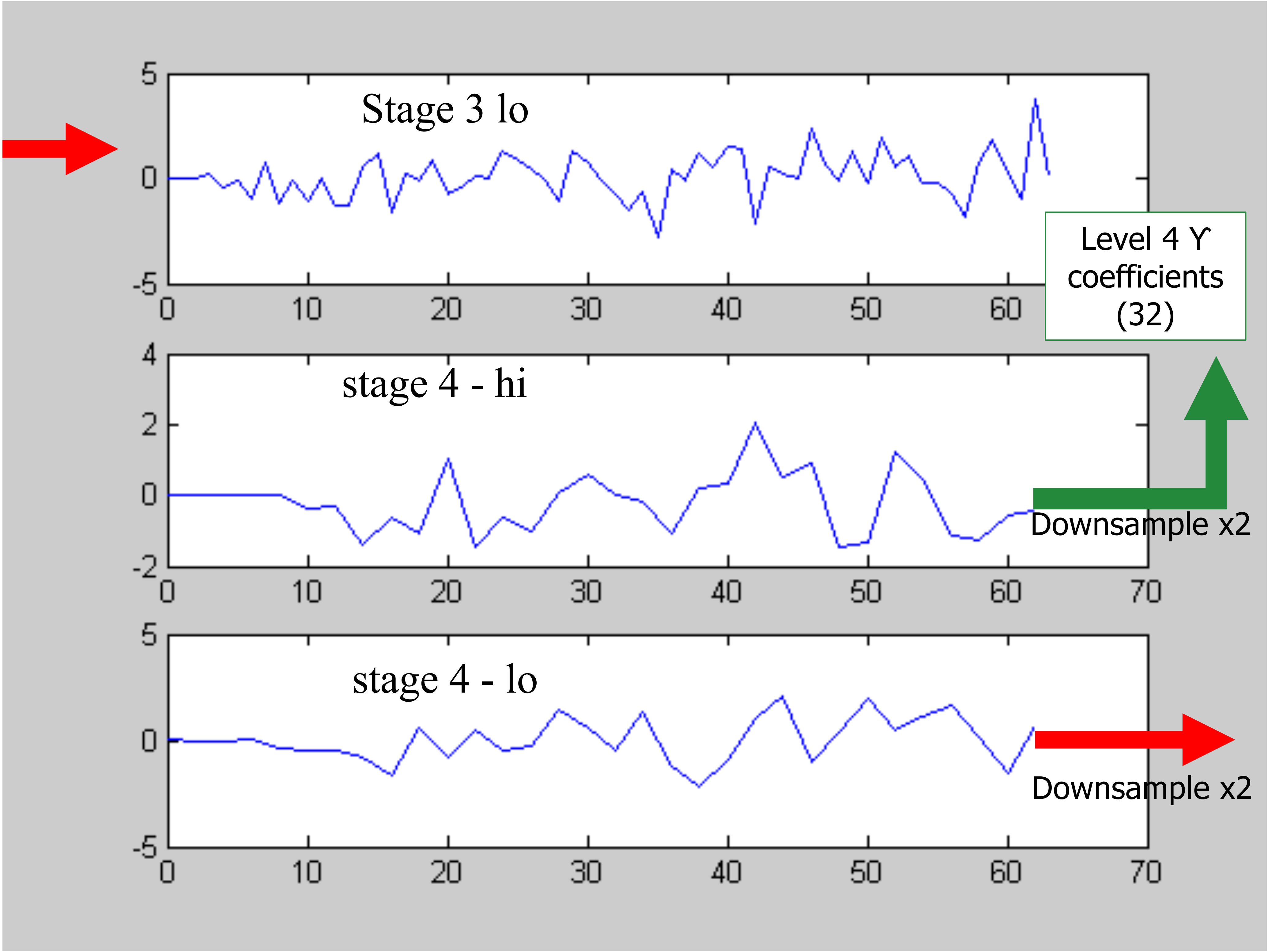
Spectrum of high pass filter

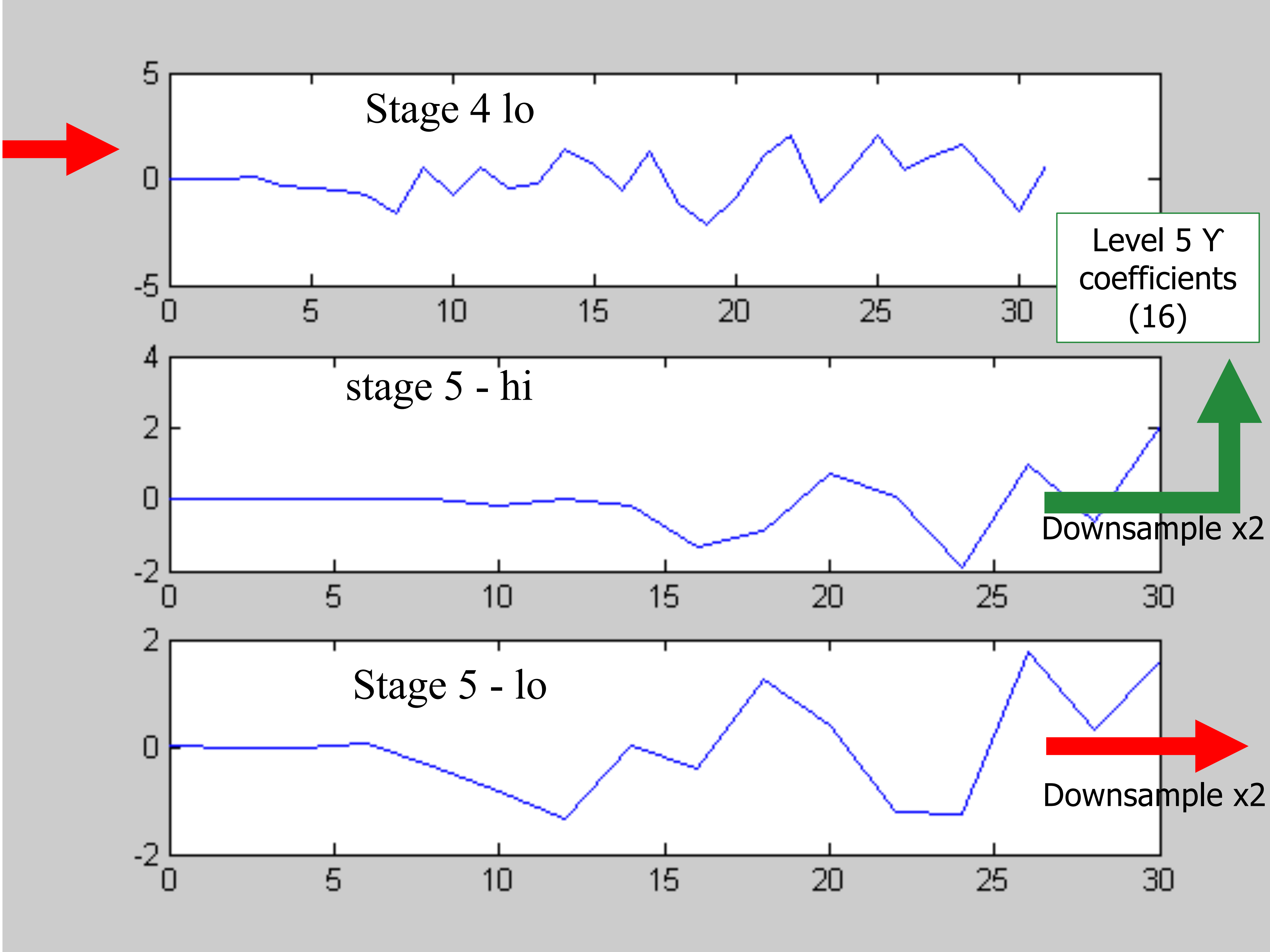



time-series
stage 1 - hi
stage 1 - lo
Level 1 Y` coefficients (256)
Downsample x2
Downsample x2
2
0
-2
1
0
-1
5
0
-5
0
100
200
300
400
500
600

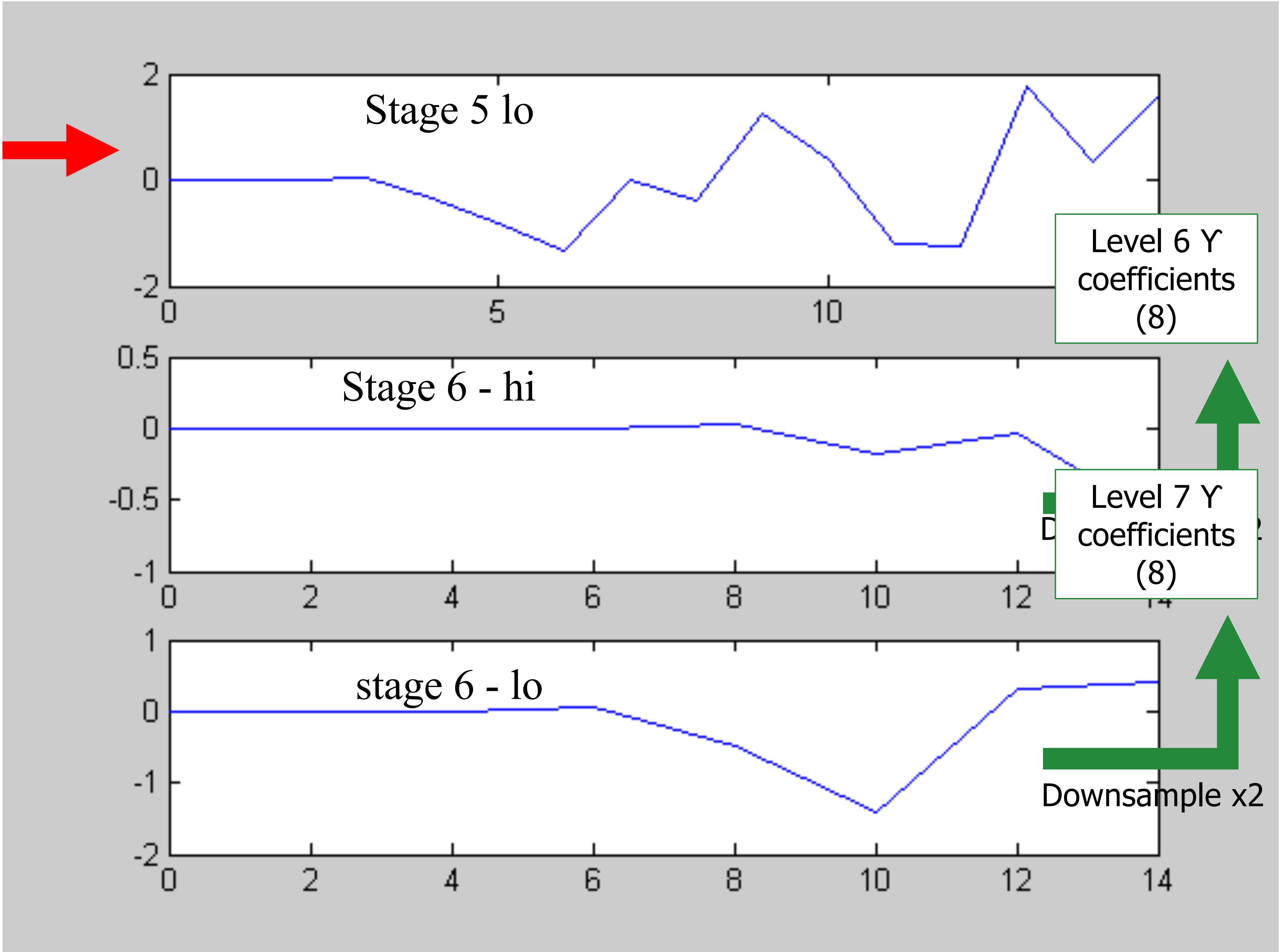

Stage 1 lo
stage 2 - hi
stage 2 - lo
Level 2 Y' coefficients (128)
Downsample x2
Downsample x2
5
0
-5
2
0
-2
5
0
-5
0
50
100
150
200
250
300


Stage 2 lo
Level 3 Y` coefficients (64)
stage 3 - hi
Downsample x2
stage 3 - lo
Downsample x2


Stage 3 lo
stage 4 - hi
stage 4 - lo
Level 4 Y` coefficients (32)
Downsample x2
Downsample x2

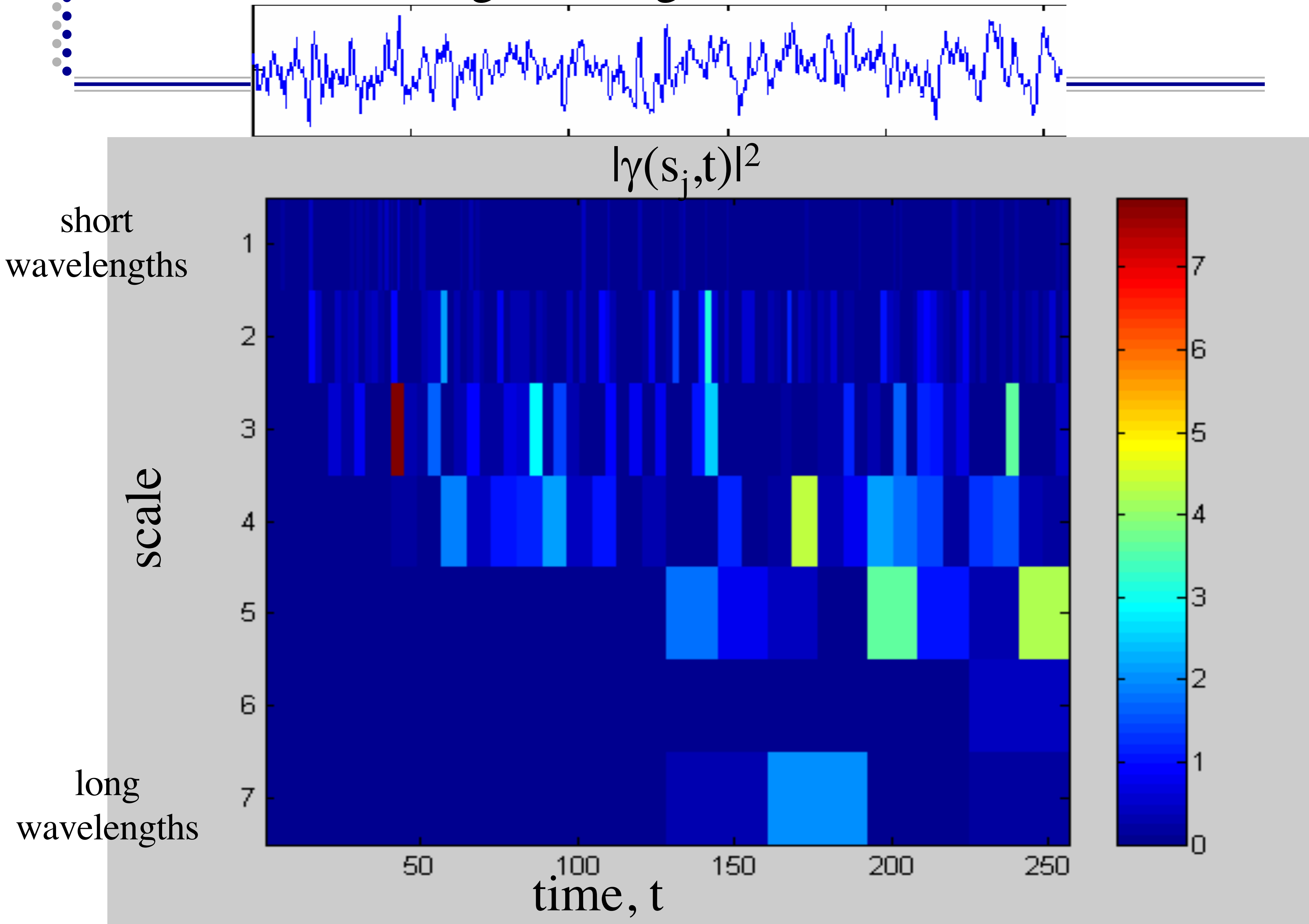


Stage 4 lo
Level 5 Y` coefficients (16)
stage 5 - hi
Downsample x2
Stage 5 - lo
Downsample x2

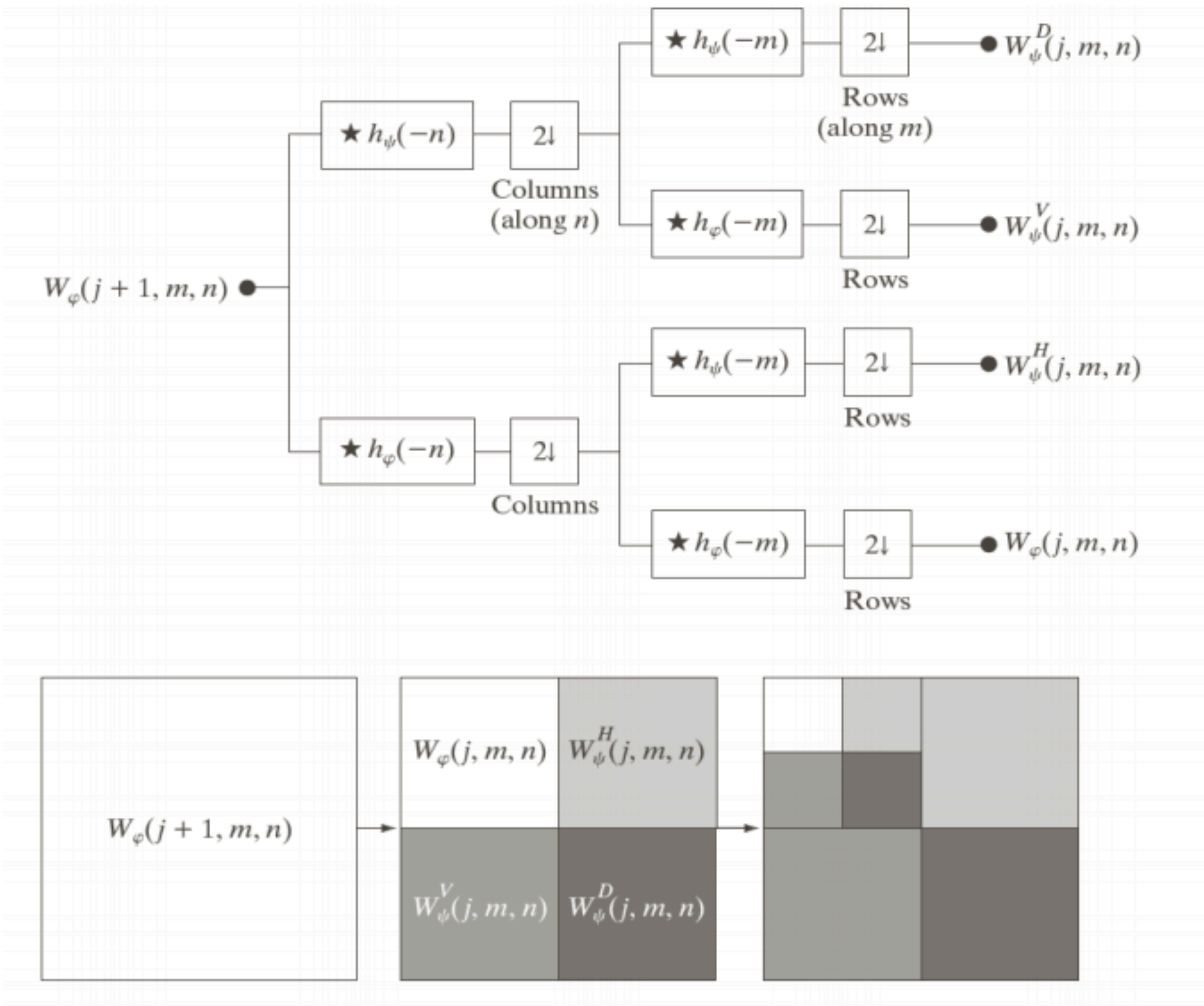


Stage 5 lo
Stage 6 - hi
stage 6 - lo
Level 6 Y
coefficients
(8)
Level 7 Y
coefficients
(8)
Downsample x2
2
0
-2
0
5
10
0.5
0
-0.5
-1
0
2
4
6
8
10
12
1
0
-1
-2
0
2
4
6
8
10
12
14

Putting it all together …



Expanding to Two Dimensions



Expanding to Two Dimensions

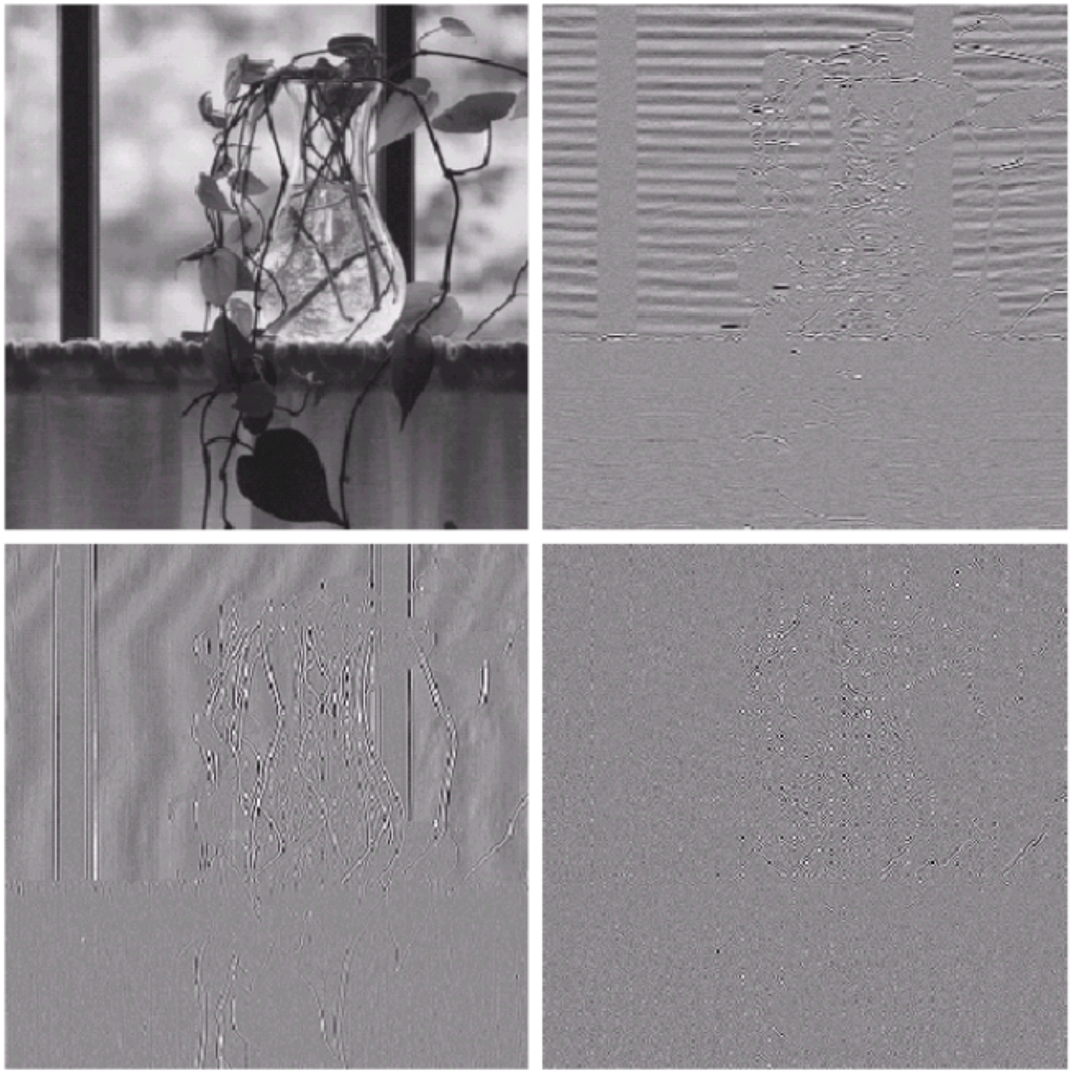


FIGURE 7.7 A four-band split of the vase in Fig. 7.1 using the subband coding system of Fig. 7.5.

a	d^V
d^H	d^D

$a(m,n)$: approximation

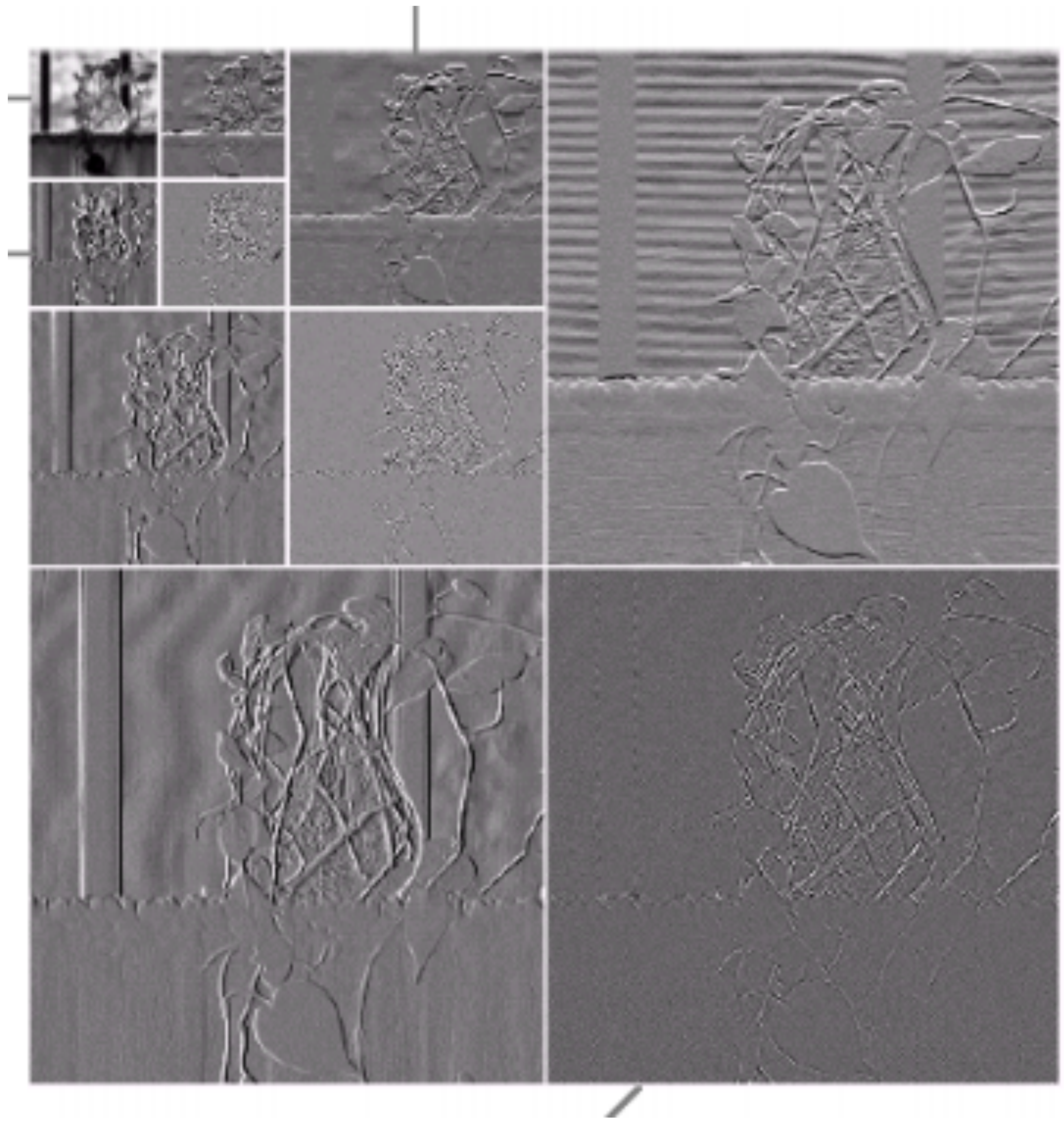
$d^V(m,n)$: detail in vertical

$d^H(m,n)$: detail in horizontal

$d^D(m,n)$: detail in diagonal

Colorado School of Mines *Image and Multidimensional Signal Processing*

Expanding to Two Dimensions



Big Ideas

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

Admin

- Project 2
  - Due 4/30
- Final Exam – 5/5
  - In Canvas
    - 2 hr window within a 12 hr time block
  - Open course notes and textbook, but cannot communicate with anyone 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 1-24*
    - Doesn't include lecture 13