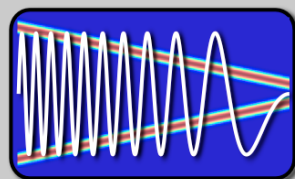


EE123



Digital Signal Processing

Lecture 10

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1

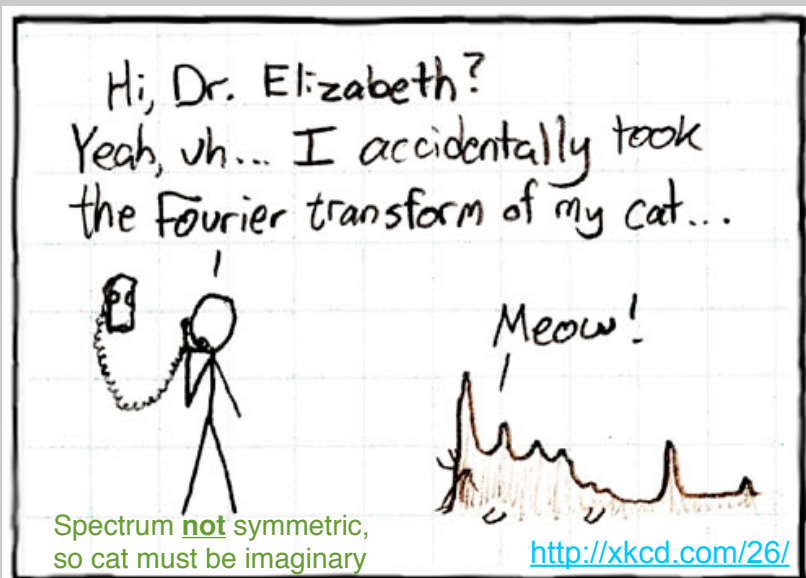
Announcements

- Office hours TA 1-2pm
- Midterm 10/12
 - All Material so far including wavelets
- Office hours attendance weak

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How do you know this guy is insane?



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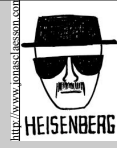
Last Time

- Frequency Tiling (Heisenberg boxes)
- Short-Time Fourier Transform
 - Equal area tiling
- Wavelets
 - Adaptive tiling

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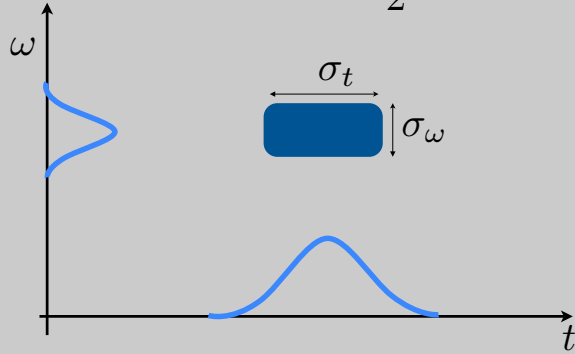
4

Heisenberg Boxes



- Time-Frequency uncertainty principle

$$\sigma_t \cdot \sigma_\omega \geq \frac{1}{2}$$



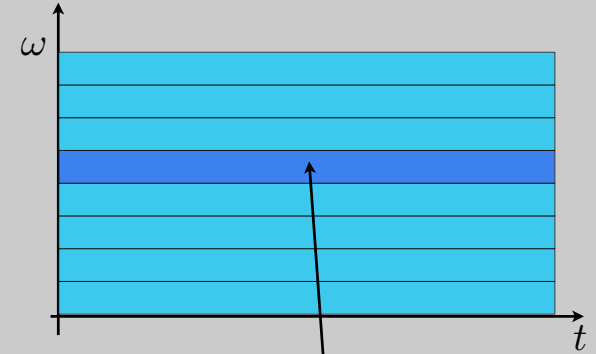
DFT

$$X[k] = \sum_{n=0}^{N-1} x[n]e^{-j2\pi kn/N}$$

$$\Delta\omega = \frac{2\pi}{N}$$

$$\Delta t = N$$

$$\Delta\omega \cdot \Delta t = 2\pi$$



one DFT coefficient

DFT

$$X[k] = \sum_{n=0}^{N-1} x[n]e^{-j2\pi kn/N}$$

$$\Delta\omega = \frac{2\pi}{N}$$

$$\Delta t = N$$

$$\Delta\omega \cdot \Delta t = 2\pi$$



Question: What is the effect of zero-padding?
 Answer: Overlapped Tiling!

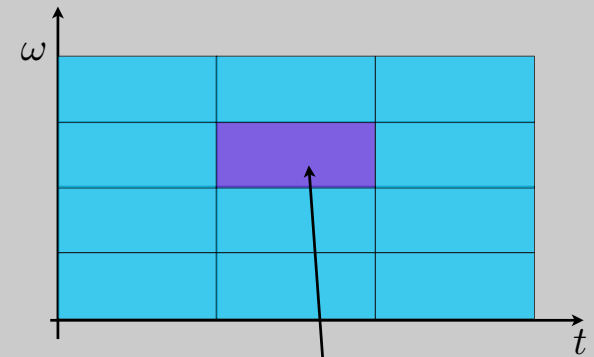
Discrete STFT

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

optional
↓

$$\Delta\omega = \frac{2\pi}{L}$$

$$\Delta t = L$$



one STFT coefficient

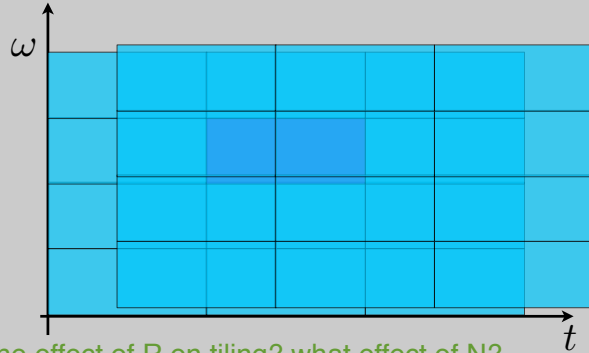
Discrete STFT

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

optional
↓

$$\Delta\omega = \frac{2\pi}{L}$$

$$\Delta t = L$$



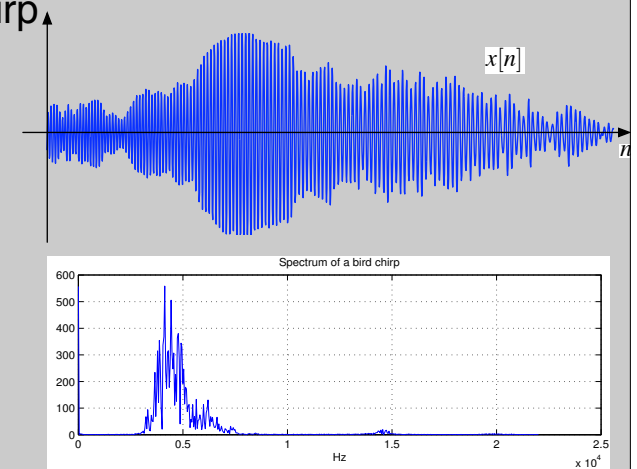
Question: What is the effect of R on tiling? what effect of N?
 Answer: Overlapping in time of frequency or both!

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Spectrogram

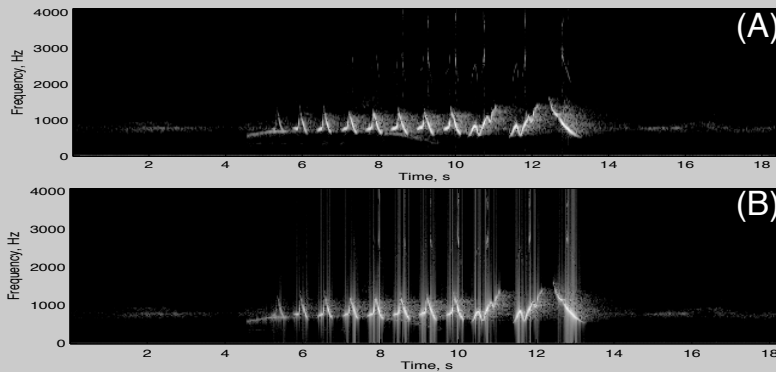
- Recall bird chirp



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Spectrogram

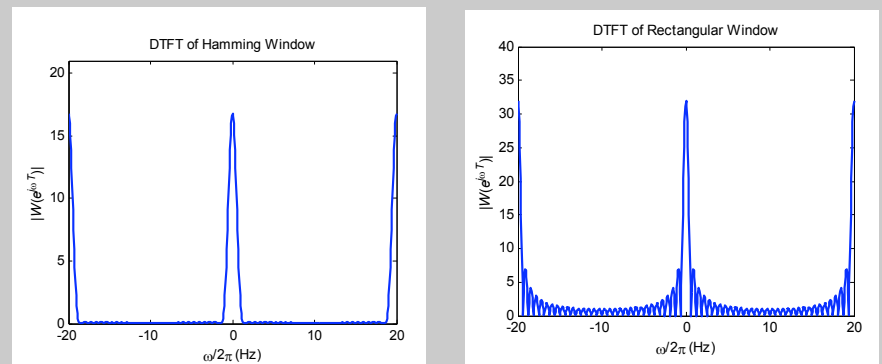


- What is the difference between the spectrograms?
 - a) Window size $B < A$
 - b) Window size $B > A$
 - c) Window type is different
 - d) (A) uses overlapping window

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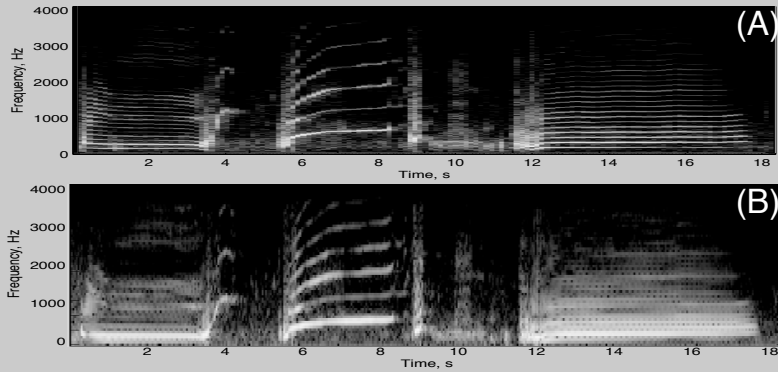
Sidelobes of Hann vs rectangular window



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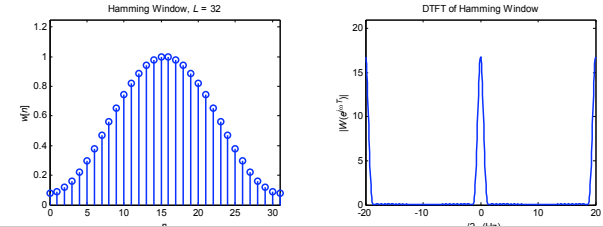
Spectrogram



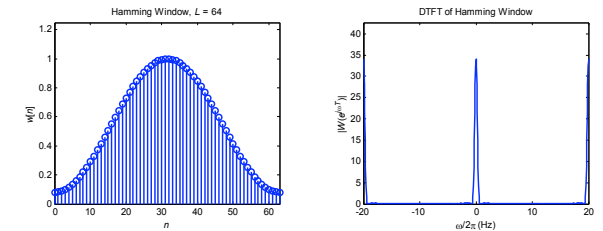
- What is the difference between the spectrograms?
 - a) Window size $B < A$
 - b) Window size $B > A$
 - c) Window type is different
 - d) (A) uses overlapping window

Spectrogram

Hamming Window, $L = 32$



Hamming Window, $L = 64$

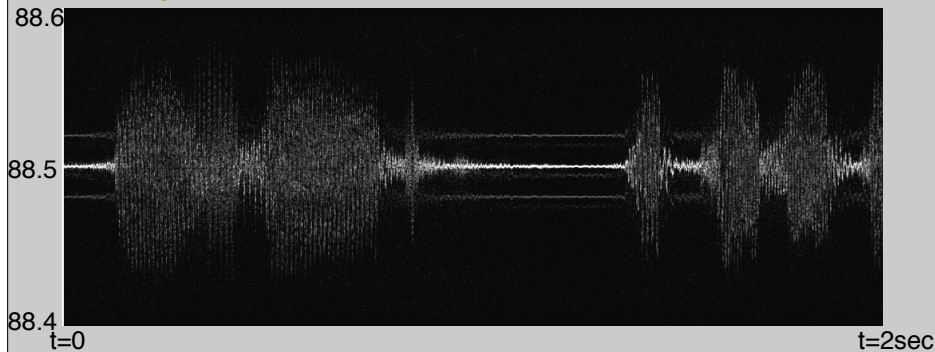


Lab 2

$$y_c(t) = A \cos\left(2\pi f_c t + 2\pi \Delta f \int_0^t x(\tau) d\tau\right)$$

$$y[n] = y(nT) = A \exp\left(j2\pi \Delta f \int_0^{nT} x(\tau) d\tau\right)$$

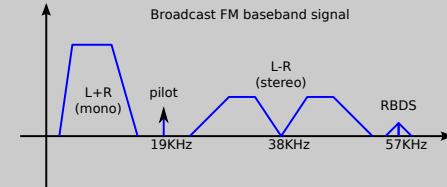
Spectrogram of FM radio



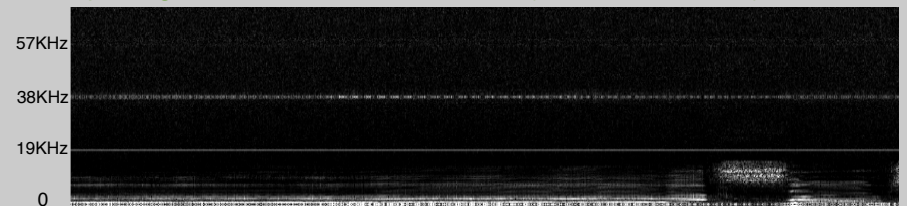
Lab 2

$$y[n] = y(nT) = A \exp\left(j2\pi \Delta f \int_0^{nT} x(\tau) d\tau\right)$$

$$x(t) = \underbrace{(L+R)}_{\text{mono}} + \underbrace{0.1 \cdot \cos(2\pi f_p t)}_{\text{pilot}} + \underbrace{(L-R) \cos(2\pi(2f_p)t)}_{\text{stereo}} + \underbrace{0.05 \cdot \text{RBDS}(t) \cos(2\pi(3f_p)t)}_{\text{digital RBDS}}$$



Spectrogram of Demodulated FM radio (Adele on 96.5 MHz)



Limitations of Discrete STFT

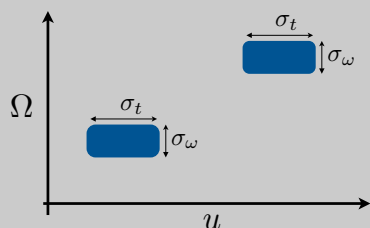
- Need overlapping \Rightarrow Not orthogonal
- Computationally intensive $O(MN \log N)$
- Same size Heisenberg boxes

From STFT to Wavelets

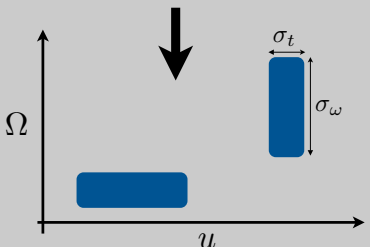
- Basic Idea:
 - low-freq changes slowly - fast tracking unimportant
 - Fast tracking of high-freq is important in many apps.
 - Must adapt Heisenberg box to frequency
- Back to continuous time for a bit.....

From STFT to Wavelets

- Continuous time



$$Sf(u, \Omega) = \int_{-\infty}^{\infty} f(t)w(t-u)e^{-j\Omega t} dt$$



$$Wf(u, s) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{s}} \Psi^* \left(\frac{t-u}{s} \right) dt$$

*Morlet - Grossmann

From STFT to Wavelets

$$Wf(u, s) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{s}} \Psi^* \left(\frac{t-u}{s} \right) dt$$

- The function Ψ is called a mother wavelet
- Must satisfy:

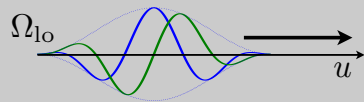
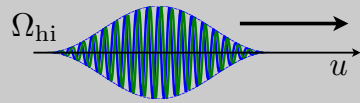
$$\int_{-\infty}^{\infty} |\Psi(t)|^2 dt = 1 \quad \Rightarrow \text{unit norm}$$

$$\int_{-\infty}^{\infty} \Psi(t) dt = 0 \quad \Rightarrow \text{Band-Pass}$$

STFT and Wavelets “Atoms”

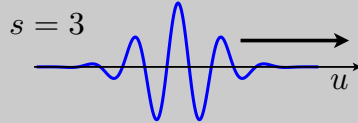
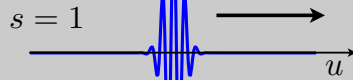
STFT Atoms

$$w(t - u)e^{j\Omega t}$$



Wavelet Atoms

$$\frac{1}{\sqrt{s}}\Psi\left(\frac{t-u}{s}\right)$$



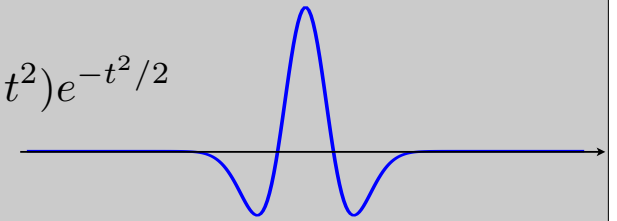
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Examples of Wavelets

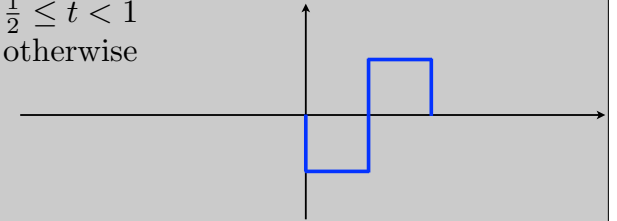
• Mexican Hat

$$\Psi(t) = (1 - t^2)e^{-t^2/2}$$



• Haar

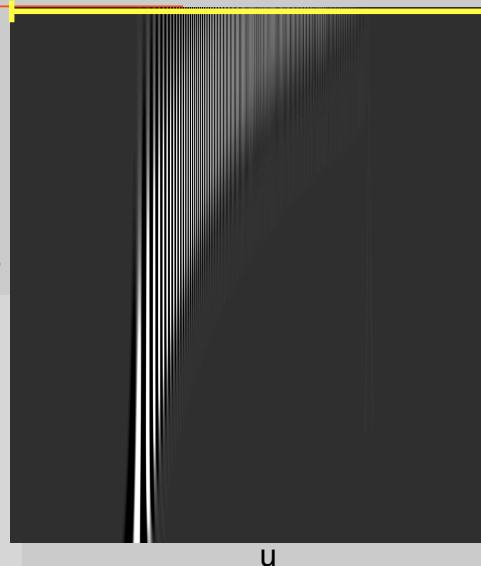
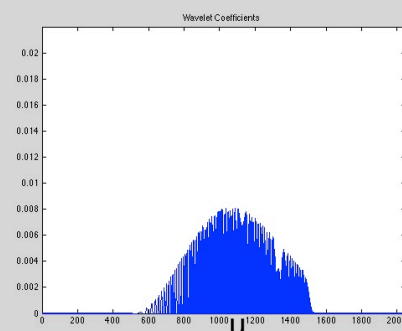
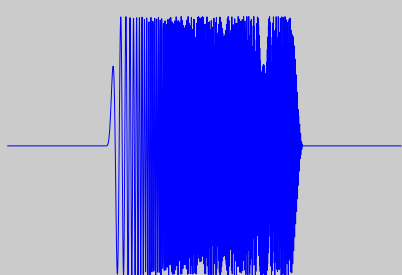
$$\Psi(t) = \begin{cases} -1 & 0 \leq t < \frac{1}{2} \\ 1 & \frac{1}{2} \leq t < 1 \\ 0 & \text{otherwise} \end{cases}$$



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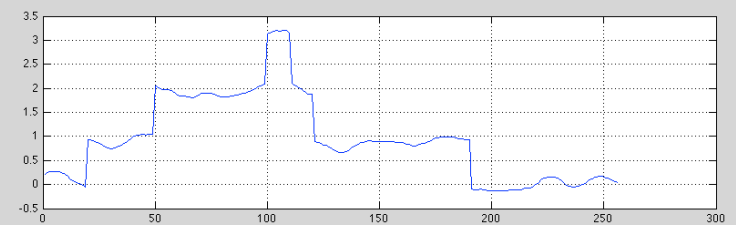
Example: Wavelet of Chirp



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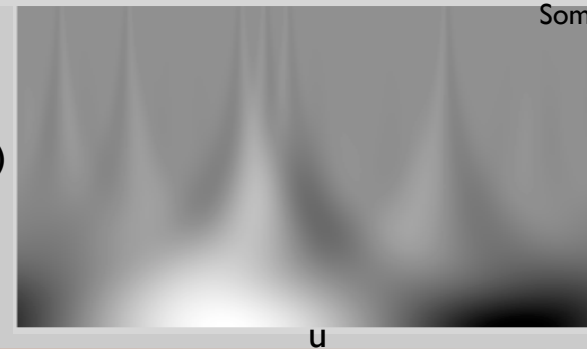
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Example 2: “Bumpy” Signal



SombreroWavelet

$\log(s)$



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Wavelets Transform

- Can be written as linear filtering

$$\begin{aligned} Wf(u, s) &= \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} f(t) \Psi^* \left(\frac{t-u}{s} \right) dt \\ &= \{ f(t) * \bar{\Psi}_s(t) \} (u) \end{aligned}$$

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

- Wavelet coefficients are a result of bandpass filtering

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Wavelet Transform

- Many different constructions for different signals
 - Haar good for piece-wise constant signals
 - Battle-Lemarie' : Spline polynomials
- Can construct Orthogonal wavelets
 - For example: dyadic Haar is orthonormal

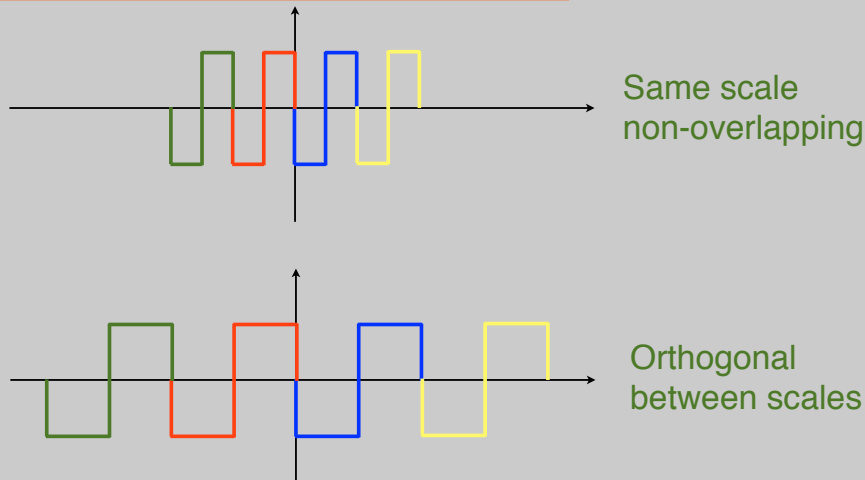
$$\bar{\Psi}_{i,n}(t) = \frac{1}{\sqrt{2^i}} \Psi \left(\frac{t - 2^i n}{2^i} \right)$$

$i = [1, 2, 3, \dots]$

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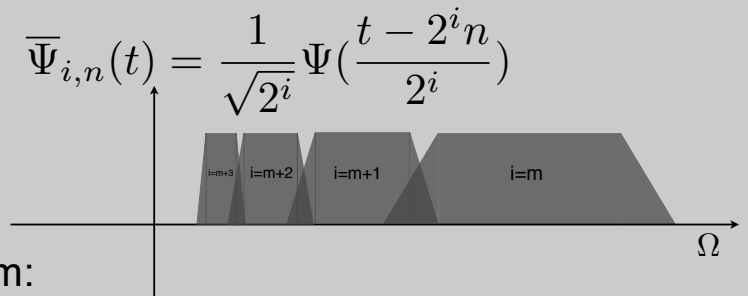
Orthonormal Haar



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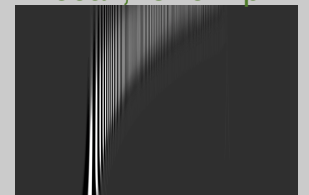
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Scaling function



- Problem:
 - Every stretch only covers half remaining bandwidth
 - Need Infinite functions

recall, for chirp:



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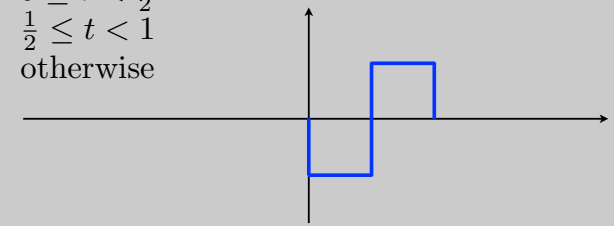
Scaling function

$$\bar{\Psi}_{i,n}(t) = \frac{1}{\sqrt{2^i}} \Psi\left(\frac{t - 2^i n}{2^i}\right)$$

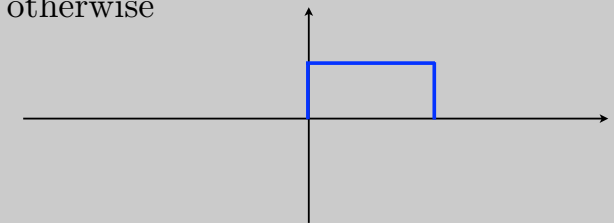
- **Problem:**
 - Every stretch only covers half remaining bandwidth
 - Need Infinite functions
- **Solution:**
 - Plug low-pass spectrum with a scaling function $\bar{\Phi}$

Haar Scaling function

$$\Psi(t) = \begin{cases} -1 & 0 \leq t < \frac{1}{2} \\ 1 & \frac{1}{2} \leq t < 1 \\ 0 & \text{otherwise} \end{cases}$$



$$\Phi(t) = \begin{cases} 1 & 0 \leq t < 1 \\ 0 & \text{otherwise} \end{cases}$$



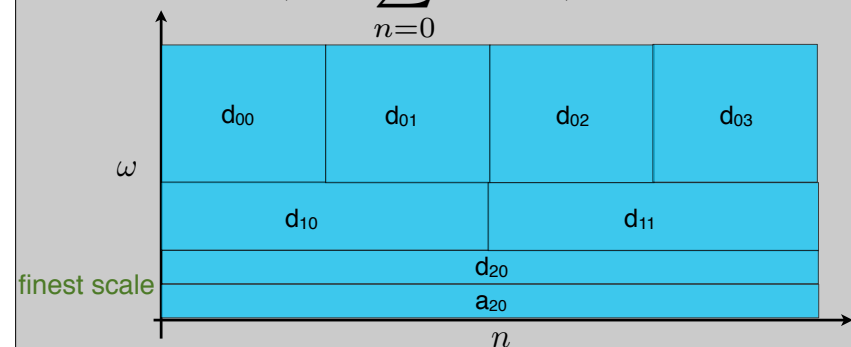
Back to Discrete

- Early 80's, theoretical work by Morlett, Grossman and Meyer (math, geophysics)
- Late 80's link to DSP by Daubechies and Mallat.
- From CWT to DWT not so trivial!
- Must take care to maintain properties

Discrete Wavelet Transform

$$d_{s,u} = \sum_{n=0}^{N-1} x[n] \Psi_{s,u}[n]$$

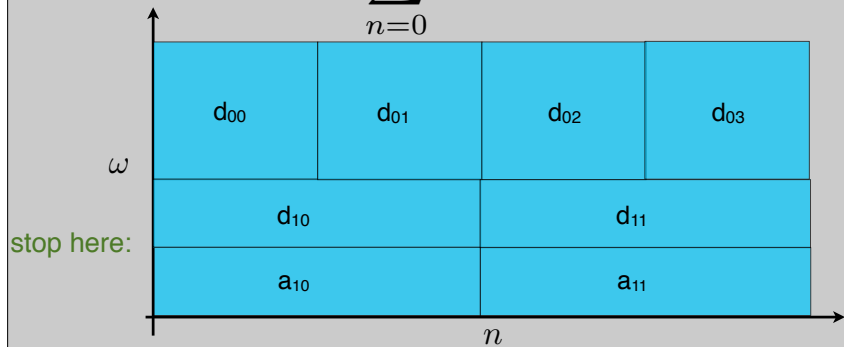
$$a_{s,u} = \sum_{n=0}^{N-1} x[n] \Phi_{s,u}[n]$$



Discrete Wavelet Transform

$$d_{s,u} = \sum_{n=0}^{N-1} x[n] \Psi_{s,u}[n]$$

$$a_{s,u} = \sum_{n=0}^{N-1} x[n] \Phi_{s,u}[n]$$

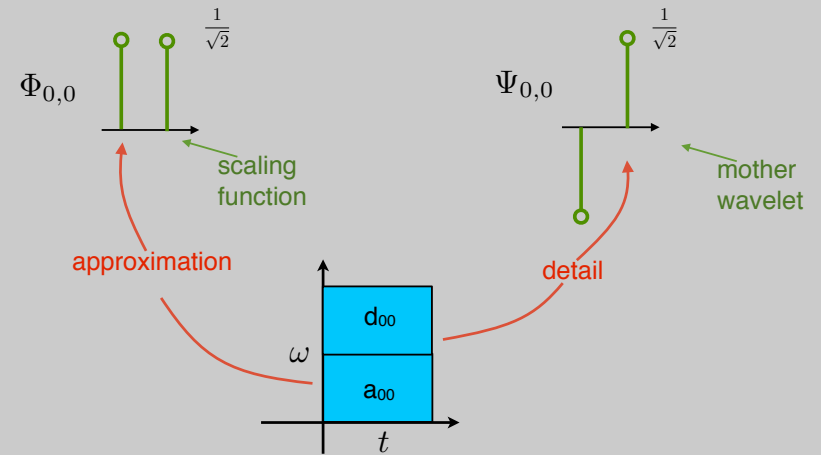


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Example: Discrete Haar Wavelet

Haar for n=2



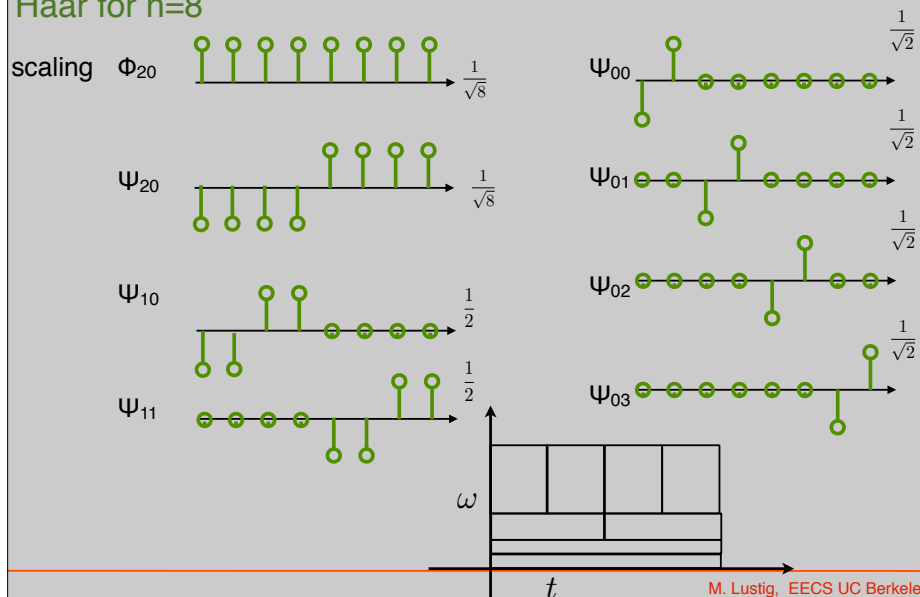
Equivalent to $DFT_2!$

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Discrete Orthogonal Haar Wavelet

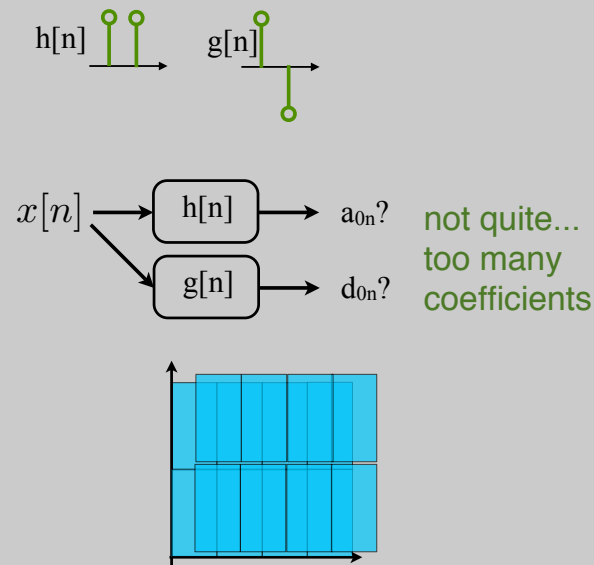
Haar for n=8



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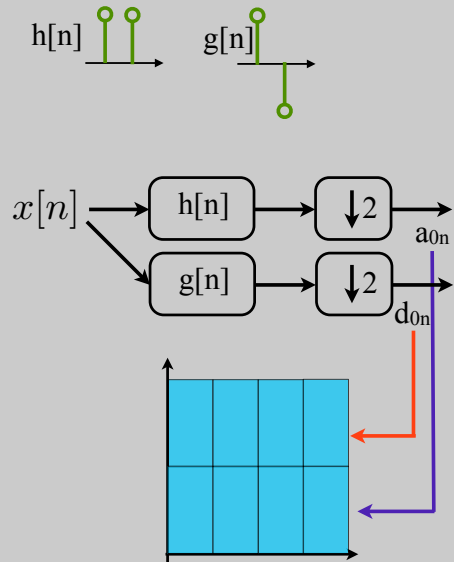
Fast DWT with Filter Banks



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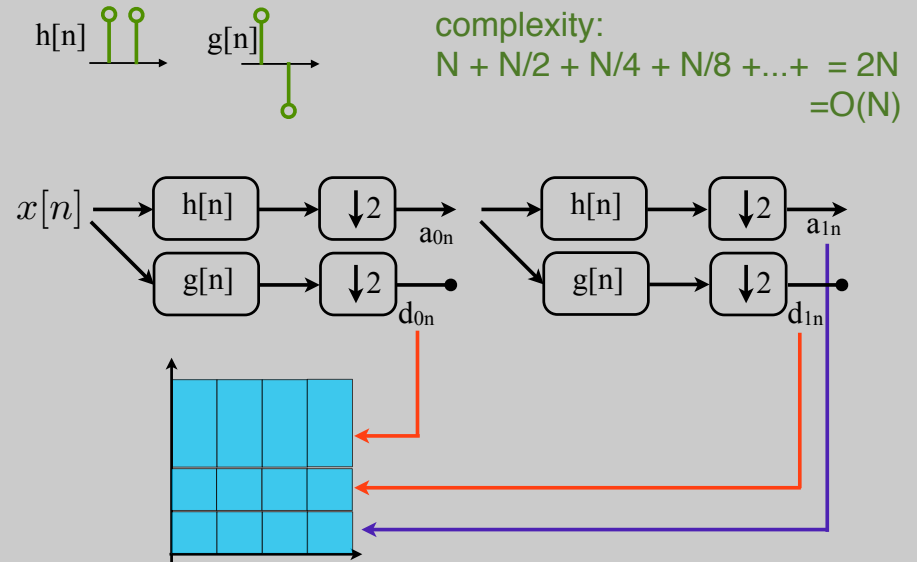
Fast DWT with Filter Banks



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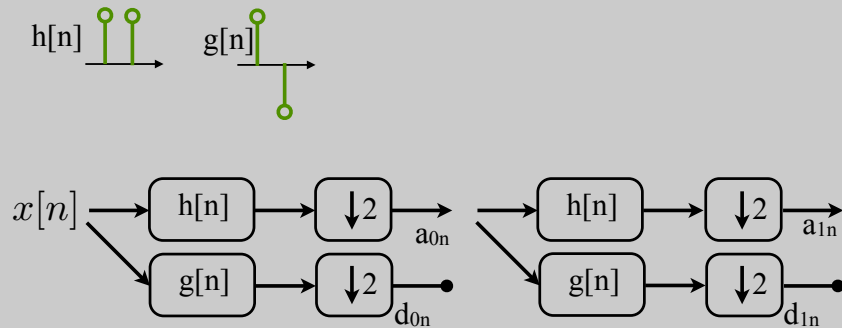
Fast DWT with Filter Banks



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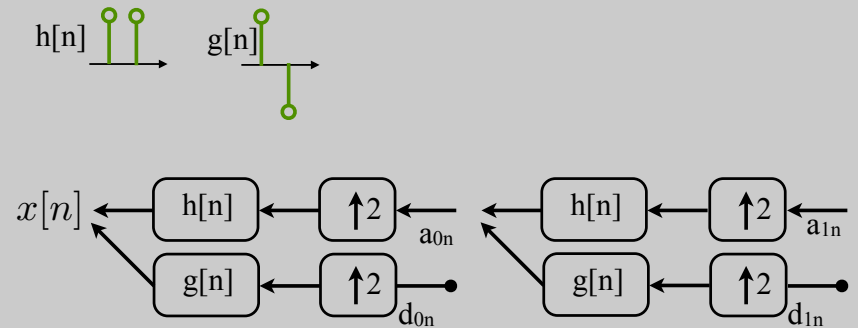
Decomposition



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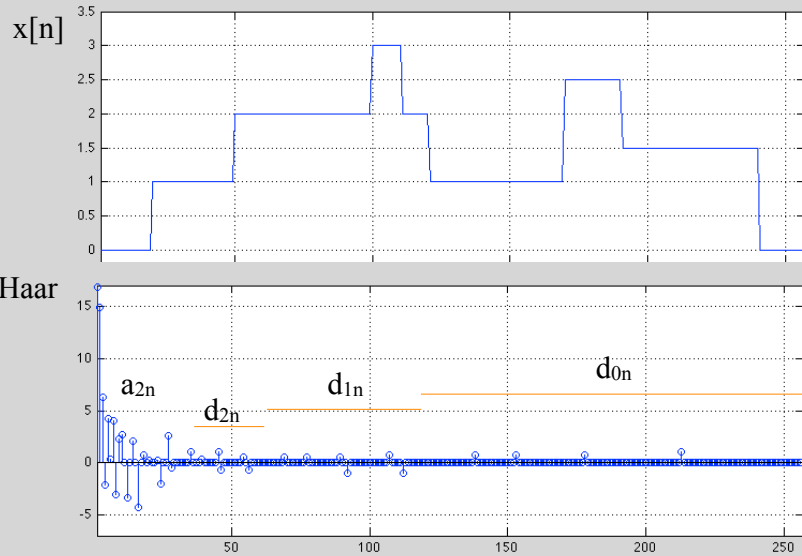
Reconstruction



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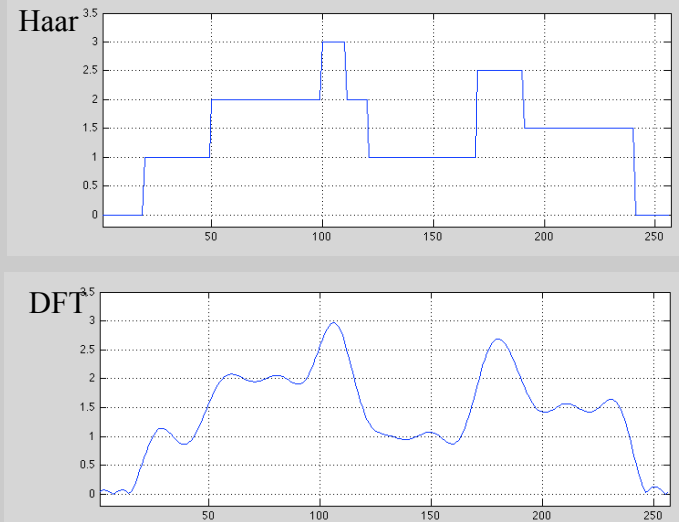
Haar DWT Example



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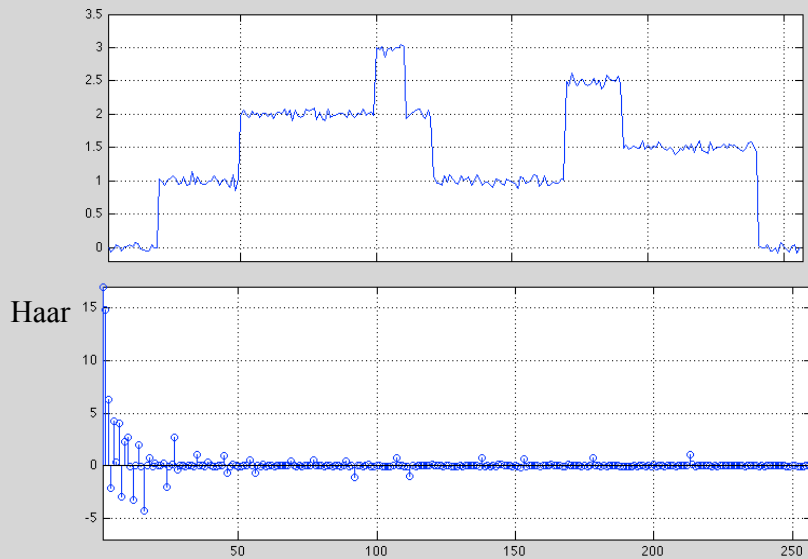
Approximation from 25/256 coefficients



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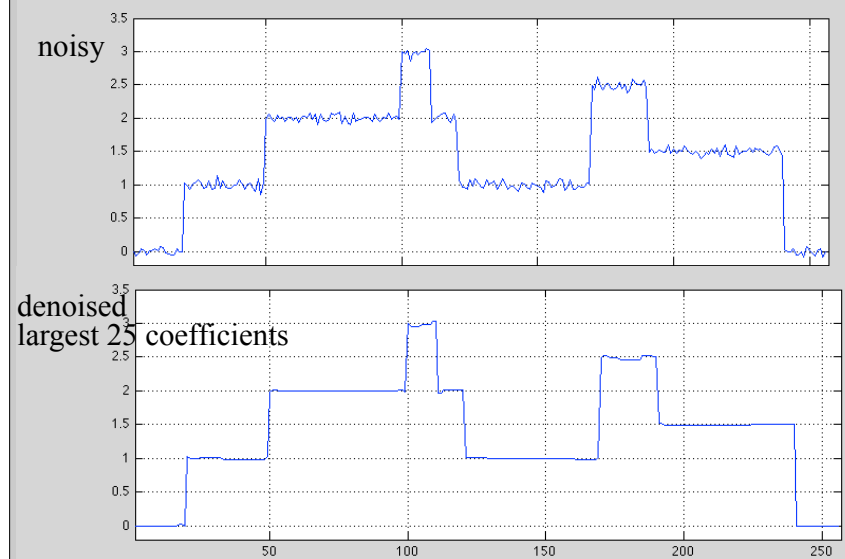
Example: Denoising Noisy Signals



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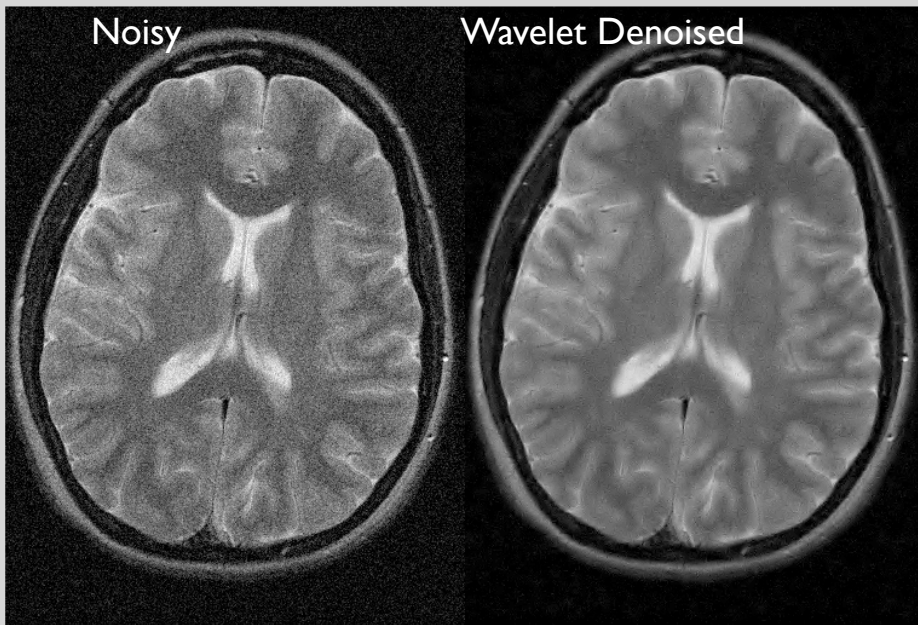
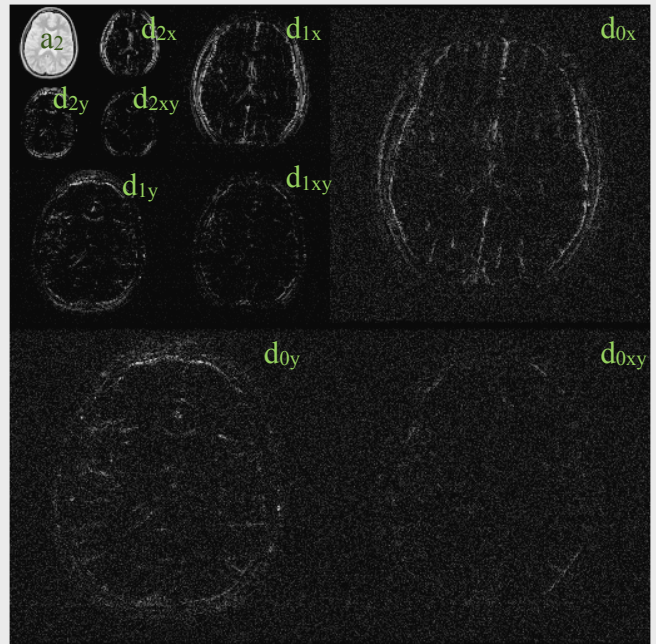
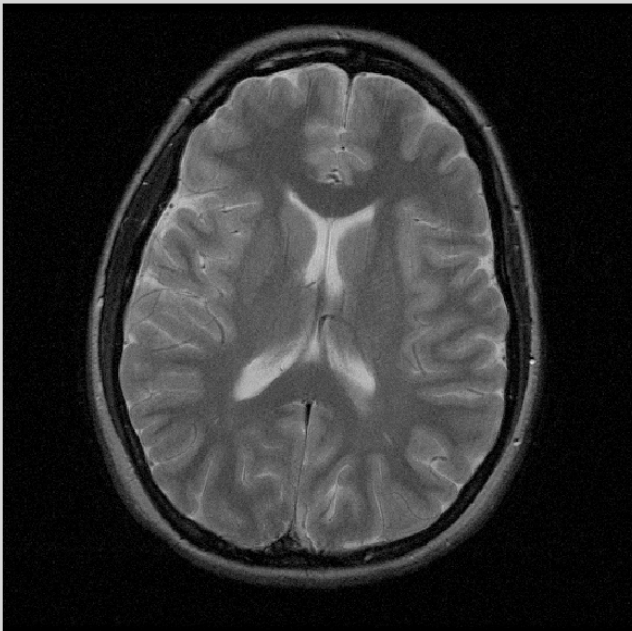
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Example: Denoising by Thresholding



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Approximation/Compression

0.000% coefficients

