

# The Dual-Tree Complex Wavelet Transform

September 6, 2007

# Outline

## Signal Processing

- Signals and Filters

- Subband Filtering Schemes with Perfect Reconstruction

## Wavelets and Subband Filtering Schemes

- Wavelets: Multiresolution Analysis

- Connection with Subband Filtering Schemes

## Problems with Real Wavelets

- Shift Variance

- Lack of directionality

## Solution

- Complex Wavelets

- The Dual-Tree Framework

# Background material. Notation and Examples

Any square summable sequence  $(c_n)_{n \in \mathbb{Z}}$  can be interpreted as the sequence of sampled values  $f(n)$  of a band-limited function  $f$  with  $\text{supp } \hat{f} \subset [-\pi, \pi]$ .

$$f(x) = \sum_{n \in \mathbb{Z}} c_n \frac{\sin \pi(x - n)}{\pi(x - n)}, \quad \hat{f}(\xi) = \sum_{n \in \mathbb{Z}} c_n e^{-in\xi}.$$

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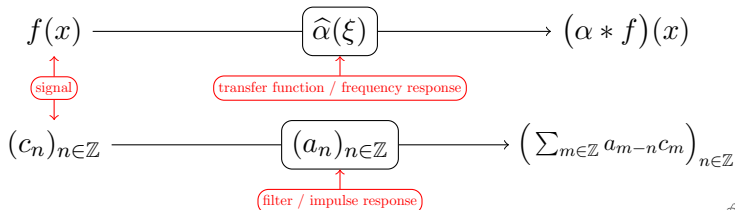
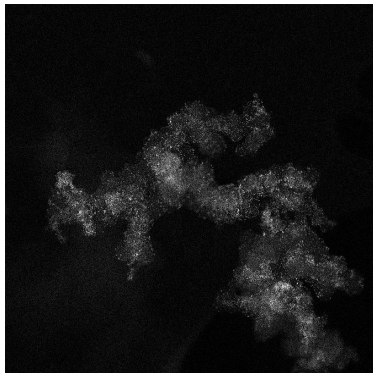
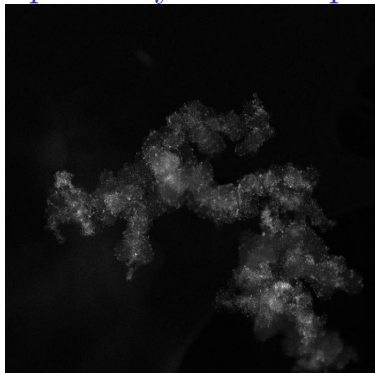
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A filtering operation corresponds to the multiplication of  $\hat{f}$  with a  $2\pi$ -periodic function,  $\hat{\alpha}(\xi) = \sum_{n \in \mathbb{Z}} a_n e^{-in\xi}$ . The result is another band-limited function:

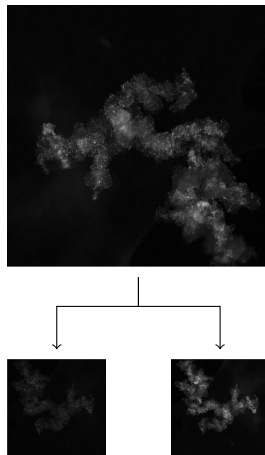
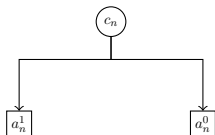
$$\begin{aligned} (\alpha * f)(x) &= \sum_{n \in \mathbb{Z}} \sum_{m \in \mathbb{Z}} a_{n-m} c_m \frac{\sin \pi(x - n)}{\pi(x - n)}, \\ \mathcal{F}(\alpha * f)(\xi) &= \sum_{n \in \mathbb{Z}} \sum_{m \in \mathbb{Z}} a_{n-m} c_m e^{-in\xi}. \end{aligned}$$

## Example: 3-by-3 unsharp contrast enhancement filter



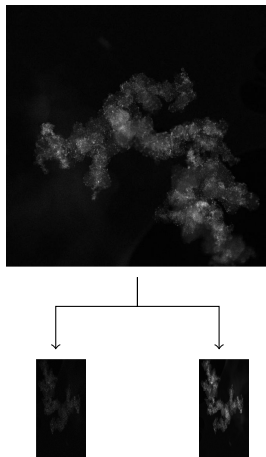
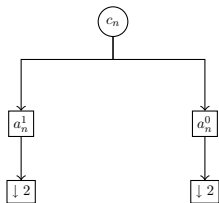
# Subband Filtering Schemes

In signal processing an incoming signal is often decomposed into different frequency bands after which they can then be coded and transmitted separately and efficiently. This decomposition of a signal is usually done using a collection of filters called a **filter bank**.

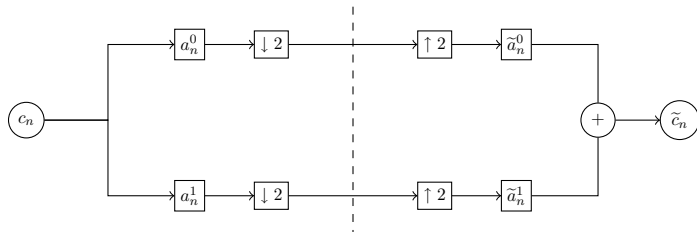


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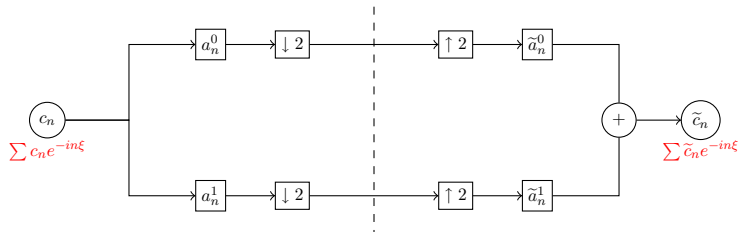


# Reconstruction

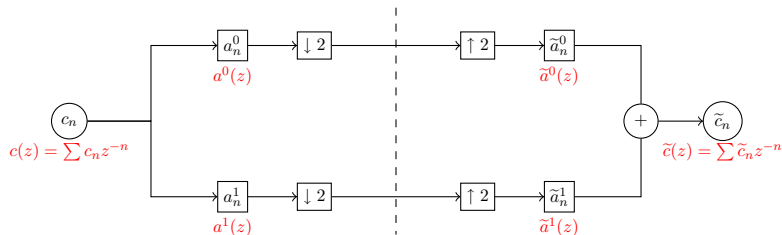




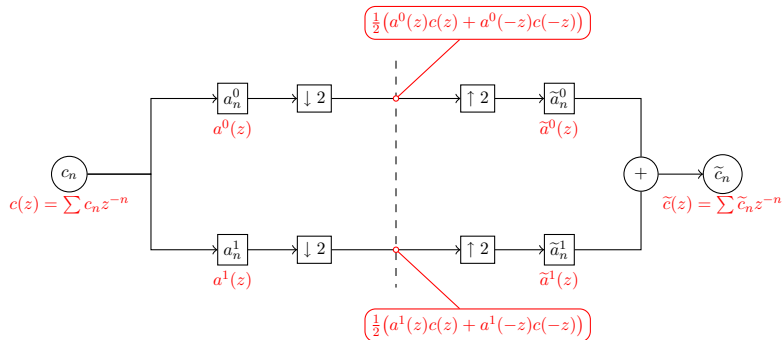
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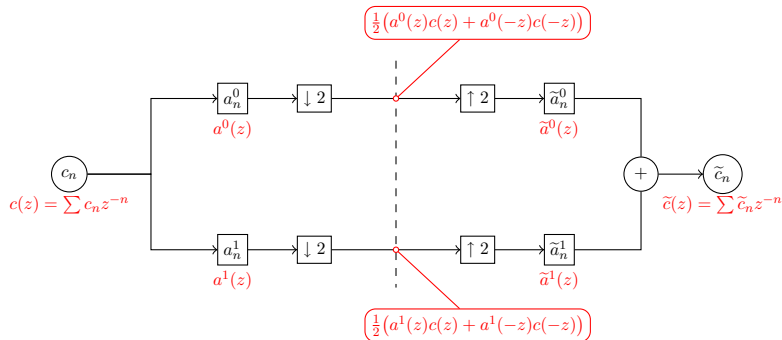
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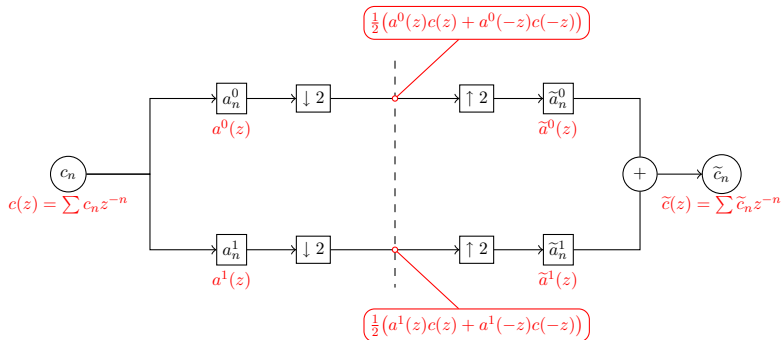


# Reconstruction



$$\tilde{c}(z) = \frac{1}{2}(\tilde{a}^0(z)a^0(z) + \tilde{a}^1(z)a^1(z))c(z) + \underbrace{\frac{1}{2}(\tilde{a}^0(z)a^0(-z) + \tilde{a}^1(z)a^1(-z))c(-z)}_{\text{aliasing effects}}$$

# Perfect Reconstruction



$$\tilde{a}^0(z)a^0(z) + \tilde{a}^1(z)a^1(z) = 2, \quad \tilde{a}^0(z)a^0(-z) + \tilde{a}^1(z)a^1(-z) = 0$$

# Wavelets

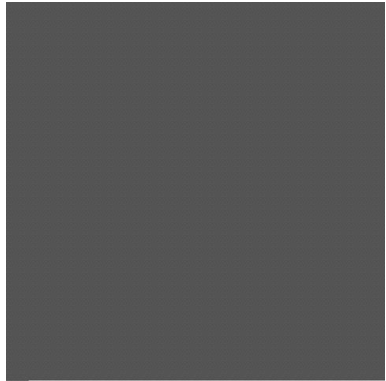


$1,024 \times 1,024 = 1,048,576$  pixels

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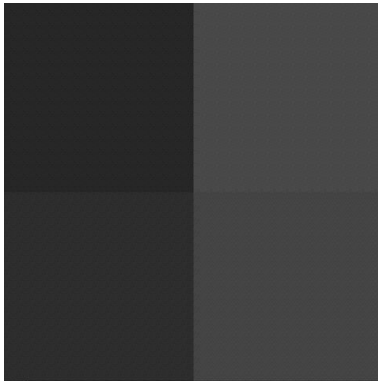


1 wavelet coefficient

# Wavelets



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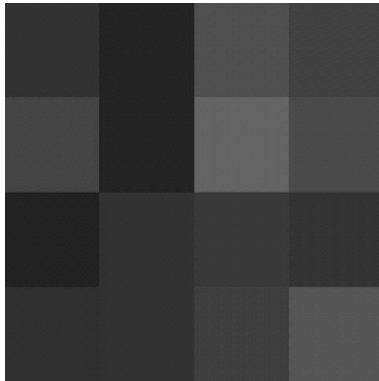
$1 + 4 = 5$  wavelet coefficients



# Wavelets



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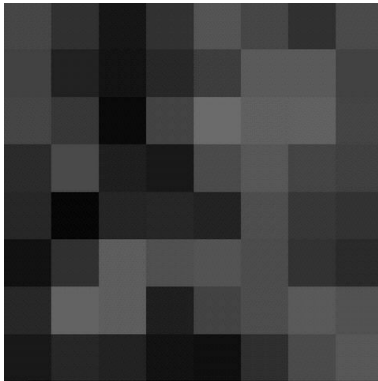


$1 + 4 + 16 = 21$  wavelet coefficients

# Wavelets



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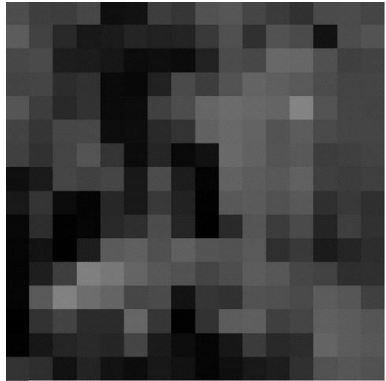


$1 + 4 + 16 + 64 = 85$  wavelet coefficients

# Wavelets



$1,024 \times 1,024 = 1,048,576$  pixels



$1 + 4 + 16 + 64 + 256 = 341$  wavelet coefficients

# Wavelets



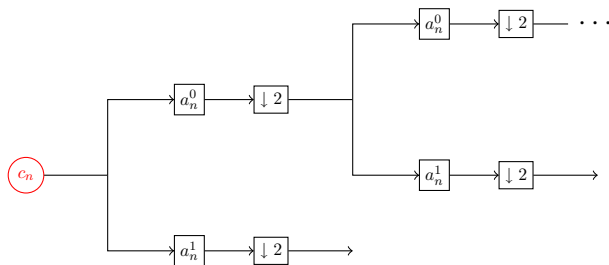
$1,024 \times 1,024 = 1,048,576$  pixels



21,845 wavelet coefficients

# Connection with Subband Filtering Schemes

Multiresolution analysis leads to a hierarchical scheme for the computation of the wavelet coefficients of a function:



# Problems with Real Wavelets

## Shift Variance

A small shift of the signal causes major variations in the distribution of energy between wavelet coefficients at different scales.

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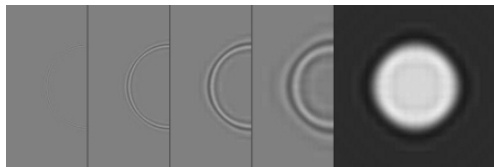
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## Poor Directional Selectivity

The standard tensor-product construction of multi-variate wavelets produces a checkerboard pattern that is simultaneously oriented along several directions. This lack of directional selectivity complicates processing of geometric image features like ridges and edges.



# Some Complex Wavelets do not have those problems!



N. Kingsbury: “Complex Wavelets for Shift Invariant Analysis and Filtering of Signals”

The key: “Hilbert Transform pairs”

Complex-valued scaling function  $\phi: \mathbb{R} \rightarrow \mathbb{C}$  and complex-valued wavelet  $\psi: \mathbb{R} \rightarrow \mathbb{C}$  satisfying

$$\psi(t) = u(t) + i\mathcal{H}u(t).$$

You get extra points if  $u: \mathbb{R} \rightarrow \mathbb{R}$  is even, and  $\mathcal{H}u$  is odd.



# Watch out! Not so easy to code

For a complex-valued function  $\psi(t) = u(t) + i\mathcal{H}u(t)$ ,

$$\begin{aligned}\widehat{\psi}(\xi) &= \widehat{u}(\xi) + i\mathcal{F}(\mathcal{H}u)(\xi) \\ &= \widehat{u}(\xi) - \text{sign}(\xi)\widehat{u}(\xi) \\ &= \begin{cases} 0 & \text{if } \xi > 0, \\ \widehat{u}(0) & \text{if } \xi = 0, \\ 2\widehat{u}(\xi) & \text{if } \xi < 0. \end{cases}\end{aligned}$$

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Neither  $a^0(z)$  nor  $\widetilde{a}^0(x)$  is a reasonable low-pass filter.

# The Dual-Tree CWT

The idea:

Require  $u(t)$  to be a real-valued wavelet such that  $\mathcal{H}u(t)$  is also a wavelet, and perform **two** different subband filtering schemes for real and imaginary parts independently.

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- ▶ The filters are real; no complex arithmetic is required for the implementation.
- ▶ The dual-tree CWT is not **critically sampled**: it is two times expansive in 1-D.
- ▶ The inverse is simple: real and imaginary parts are inverted to obtain two real signals. These two signals are then averaged.