

# Image Analysis

4. Wavelets

Lars Schmidt-Thieme

Information Systems and Machine Learning Lab (ISMLL) Institute for Business Economics and Information Systems & Institute for Computer Science University of Hildesheim http://www.ismll.uni-hildesheim.de

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**Image Analysis** 



**1. Haar Wavelets** 

- 2. Daubechies Wavelets
- 3. Two-dimensional Wavelets

#### **Basis Functions**



#### Fourier Analysis:

#### Wavelets:



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Image Analysis / 1. Haar Wavelets

#### **Basis Functions**

Fourier Analysis:

#### Wavelets:

$$\begin{split} \psi_{\omega}(x) &:= \cos 2\pi\omega x \qquad \psi_{s,t}(x) := \sqrt{2^{s}} \cdot \mathsf{haar}(2^{s}x - t) \\ &= \sqrt{2^{s}} \cdot \begin{cases} 1, \ x \in (2^{-s}t, 2^{-s}(t + \frac{1}{2})) \\ -1, \ x \in [2^{-s}(t + \frac{1}{2}), 2^{-s}(t + 1)) \\ 0, \ \mathsf{else} \end{cases} \\ \\ \mathbf{0} \\ \mathbf{2^{-st}} \quad \mathbf{2^{-s}(t+1/2)} \quad \mathbf{2^{-s}(t+1)} \end{split}$$



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Image Analysis / 1. Haar Wavelets

#### Orthogonality of Basis Functions

Obviously, two distinct Haar basis functions  $\psi_{s,t}$  and  $\psi_{s',t'}$  with  $s, t, s', t' \in \mathbb{Z}$  are orthogonal:

$$\langle \psi_{s,t}, \psi_{s',t'} \rangle := \int_{-\infty}^{\infty} \psi_{s,t}(x) \cdot \psi_{s',t'}(x) \, dx = 0$$

And

$$\langle \psi_{s,t}, \psi_{s,t} \rangle = 1$$

Proof.

If they have the same scale (s = s'), then their support does not overlap.

If they have different scale, say s > s', then  $\psi_{s,t}$  is constant on the support of  $\psi_{s',t'}$ , i.e., the integral averages to zero.

 $\langle \psi_{s,t}, \psi_{s,t} \rangle$  integrates  $\sqrt{2^s} \cdot \sqrt{2^2} = 2^s$  over the support  $2^{-s}$ .



#### Wavelet Representation



Theorem (Wavelet Representation). Let  $\psi_{s,t}$ ,  $s, t \in \mathbb{Z}$  be a set of Wavelet basis functions.

Every function  $f : \mathbb{R} \to \mathbb{R}$  (satisfying some regularity conditions) can be written as

$$f(x) = \sum_{s \in \mathbb{Z}} \sum_{t \in \mathbb{Z}} c_{s,t} \psi_{s,t}(x)$$

with coefficients  $c_{s,t} \in \mathbb{R}$ .

The coefficients  $c_{s,t}$  can be computed as follows:

$$c_{s,t} = \int_{-\infty}^{\infty} f(x)\psi_{s,t}(x)dx$$

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Image Analysis / 1. Haar Wavelets

#### Haar Wavelet Representation



For the Haar basis functions this yields

$$f(x) = \sum_{s \in \mathbb{Z}} \sum_{t \in \mathbb{Z}} c_{s,t} \cdot \sqrt{2^s} \operatorname{haar}(2^s x - t)$$

and

$$c_{s,t} = \sqrt{2^s} \left( \int_{2^{-s}t}^{2^{-s}(t+\frac{1}{2})} f(x) \, dx - \int_{2^s(t+\frac{1}{2})}^{2^{-s}(t+1)} f(x) \, dx \right)$$

## Haar Wavelets / Computing Coefficients

John Provide Alight

The values of integrals with a simple rectangle impulse on different scales can be computed recursively:

$$a_{s,t} := \sqrt{2^s} \int_{2^{-s}t}^{2^{-s}(t+1)} f(x) \, dx$$
$$a_{s,t} = \frac{1}{\sqrt{2}} \left( a_{s+1,2t} + a_{s+1,2t+1} \right)$$

The coefficients of the Haar wavelet can be computed from these values via

$$c_{s,t} = \frac{1}{\sqrt{2}} \left( a_{s+1,2t} - a_{s+1,2t+1} \right)$$

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Image Analysis / 1. Haar Wavelets

## Haar Wavelets / Discrete Wavelet Transform

2003

For a finite discrete signal f of length  $2^n$  the function can already be represented by a finite sum of Haar wavelets:

$$f(x) = a_{-n,0} + \sum_{s=-n}^{-1} \sum_{t=0}^{2^{n+s}-1} c_{s,t} \cdot \sqrt{2^s} \operatorname{haar}(2^s x - t)$$

i.e., a composition of Haar wavelets with supports 2, 4, 8 etc.

The initial *a* values are just the signal values:

$$a_{s=0,t} := \int_{2^{-s}t}^{2^{-s}(t+1)} f(x) \, dx$$
$$= \int_{t}^{t+1} f(x) \, dx$$
$$= \sum_{x=t}^{$$

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Let

f = (1, 3, 4, 4, 2, 0, 2, 1)

Then the discrete Haar wavelet transform of f can be computed as follows:

	t							
S	0	1	2	3	4	5	6	7
$a_0 = f$	1	3	4	4	2	0	2	1
$a_{-1}$	2.83	5.66	1.41	2.12	_	_	_	_
$c_{-1}$	-1.41	0.00	1.41	0.71	—	—	—	—
$a_{-2}$	6	2.5	_	_	_	_	_	_
$c_{-2}$	-2	-0.5	—	—	—	—	—	_
$a_{-3}$	6.01	_	—	_	—	—	—	_
<i>C</i> <sub>-3</sub>	2.47	—	—	—	—	—	—	—

 $\mathsf{DWT}_{\mathsf{haar}}(f) = (6.01, 2.47, -2, -0.5, -1.41, 0.00, 1.41, 0.71)$ 

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Image Analysis / 1. Haar Wavelets

# Haar Wavelets / Computing Coefficients / Example



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# Haar Wavelets / Computing Coefficients / Example





2003



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# Haar Wavelets / Computing Coefficients



```
i dwt-haar(sequence f = (f(x))_{x=0,...,2^{n}-1}):
2 c := (c_{s,t})_{s=0,\dots,n-1; t=0,\dots,2^s-1} := 0
3 a := (a_{s,t})_{s=0,\dots,n; t=0,\dots,2^s-1} := 0
 4 a_{n,t} := f(t), \quad t = 0, \dots, 2^n - 1
 5 \text{ <u>for</u>} s := n - 1, \dots, 0 \text{ <u>do</u>}
         for t := 0, \ldots, 2^s - 1 do
 6
              a_{s,t} := (a_{s+1,2t} + a_{s+1,2t+1})/\sqrt{2}
 7
              c_{s,t} := (a_{s+1,2t} - a_{s+1,2t+1})/\sqrt{2}
 8
 9
         od
10 od
11 return (a_{0,0}, c)
```

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Image Analysis / 1. Haar Wavelets

#### Haar Wavelets / Inverse Discrete Wavelet Transform

The DWT easily can be inverted: from

$$a_{s,t} = \frac{1}{\sqrt{2}} \left( a_{s+1,2t} + a_{s+1,2t+1} \right)$$
$$c_{s,t} = \frac{1}{\sqrt{2}} \left( a_{s+1,2t} - a_{s+1,2t+1} \right)$$

we get

$$a_{s+1,2t} = \sqrt{2} (a_{s,t} + c_{s,t})/2$$
$$a_{s+1,2t+1} = \sqrt{2} (a_{s,t} - c_{s,t})/2$$

## Haar Wavelets / Inverse Discrete Wavelet Transform



```
i \text{ idwt-haar}(\text{coefficients } c = (c_{s,t})_{s=0,\dots,n-1; t=0,\dots,2^{s}-1}, a'):
2 a := (a_{s,t})_{s=0,\dots,n; t=0,\dots,2^{s}-1} := 0
3 a_{0,0} := a'
4 \text{ for } s := 0, \dots, n-1 \text{ do}
5 \text{ for } t := 0, \dots, 2^{s} - 1 \text{ do}
6 a_{s+1,2t} := (a_{s,t} + c_{s,t})/\sqrt{2}
7 a_{s+1,2t+1} := (a_{s,t} - c_{s,t})/\sqrt{2}
8 \text{ od}
9 \text{ od}
10 f := (f(x))_{x=0,\dots,2^{n}-1} := a_{n,x}, \quad x = 0, \dots, 2^{n} - 1
11 \text{ return } f
```

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Image Analysis



#### 1. Haar Wavelets

**2. Daubechies Wavelets** 

3. Two-dimensional Wavelets

### Haar Wavelets / Matrix Notation

A single iteration from scale s + 1 to s of the discrete Haar wavelet transform can be described by matrix multiplication:

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Image Analysis / 2. Daubechies Wavelets

#### Daubechies Wavelets / Definition

Ingrid Daubechies (\*1954) generalized the Haar wavelets to a family of wavelets now called **Daubechies wavelets**  $D_k$ :



The coefficients  $w_0, w_1, \ldots, w_{k-1}$  are called the **wavelet filter** coefficients.

#### Daubechies Wavelets / Definition



The matrix  $D_k$  should satisfy two conditions: 1. Orthogonality, i.e.,  $D_k D_k^T = 1$ :  $\sum_{i=0}^{k-1} w_i^2 = 1$ 

$$\sum_{i=0}^{k-1-2m} w_i w_{2m+i} = 0, \quad m = 1, 2, \dots, k/2 - 1$$

2. Approximation of order k/2, i.e., the first k/2 moments vanish.

For  $D_4$  this means:

$$w_3 - w_2 + w_1 - w_0 = 0$$
  
$$0w_3 - 1w_2 + 2w_1 - 3w_0 = 0$$

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Image Analysis / 2. Daubechies Wavelets

#### Daubechies Wavelets / Definition



In general, this are k conditions for the k coefficients of  $D_K$  leading to a unique solution:

$$\begin{split} w(D_2) &= (\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}) \\ w(D_4) &= (\frac{1+\sqrt{3}}{4\sqrt{2}}, \frac{3+\sqrt{3}}{4\sqrt{2}}, \frac{3-\sqrt{3}}{4\sqrt{2}}, \frac{1-\sqrt{3}}{4\sqrt{2}}) \end{split}$$

 $D_2$  is the Haar wavelet.

 $w(D_6)$  also can be computed analytically; the coefficients of the higher order Daubechies wavelets can only be computed numerically.

#### Daubechies Wavelets / DWT Algorithm



1 dwt-daubechies(sequence  $f = (f(x))_{x=0,\dots,2^n-1}, k)$ : 2  $w := (w(x))_{x=0,\dots,k-1} := \text{getDaubechiesWaveletCoefficients}(k)$  $c := (c_{s,t})_{s=0,\dots,n-1:t=0,\dots,2^{s}-1} := 0$ 4  $a := (a_{s,t})_{s=0,\dots,n;\ t=0,\dots,2^s-1} := 0$ 5  $a_{n,t} := f(t), \quad t = 0, \dots, 2^n - 1$ 6 for  $s := n - 1, \ldots, 0$  do for  $t := 0, \ldots, 2^s - 1$  do 7  $a_{s,t} := 0$ 8  $c_{s,t} := 0$ 9 for x := 0, ..., k - 1 do 10  $a_{s,t} := a_{s,t} + a_{s+1,2t+x \mod 2^{s+1}} w(x)$ 11  $c_{s,t} := c_{s,t} + a_{s+1,2t+x \mod 2^{s+1}} (-1)^x w(k-1-x)$ 12 13 od 14 od 15 od 16 **return**  $(a_{0,0}, c)$ 

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Image Analysis / 2. Daubechies Wavelets

#### Generic DWT Algorithm (1/2)



1 dwt-generic(sequence  $f = (f(x))_{x=0,\dots,2^n-1}$ , wavelet transform W): 2  $c := (c_{s,t})_{s=0,\dots,n-1; t=0,\dots,2^s-1} := 0$ 3  $a := (a_{s,t})_{s=0,\dots,n; t=0,\dots,2^s-1} := 0$ 4  $a_{n,t} := f(t), \quad t = 0, \dots, 2^n - 1$ 5 for  $s := n - 1, \ldots, 0$  do  $(c_{s_{1}}, a_{s_{2}}) := dwt\text{-iteration}(a_{s+1_{1}}, W)$ 6 7 **od** 8 <u>**return**</u>  $(a_{0,0}, c)$ 9 10 dwt-iteration(sequence  $f = (f(x))_{x=0,\dots,2^{n+1}-1}$ , wavelet transform W): 11  $a := (a_t)_{t=0,\dots,2^n-1} := 0$ 12  $c := (c_t)_{t=0,\dots,2^n-1} := 0$ 13 for  $t := 0, \dots, 2^n - 1$  do  $(a_t, c_t) := W((f_{2t+x \mod 2^{n+1}})_{x=0,\dots,2^{n+1}-1})$ 14 15 **od** *16* return (c, a)

#### Generic DWT Algorithm (2/2)



1 W-haar(sequence  $a = (a(t))_{t=0,...,2^{n}-1}$ ): 2 <u>return</u>  $((a_{0} + a_{1})/\sqrt{2}, (a_{0} - a_{1})/\sqrt{2})$ 3 4 W-daubechies-k(sequence  $a = (a(t))_{t=0,...,2^{n}-1}$ ): 5  $w := (w(x))_{x=0,...,k-1}$  := getDaubechiesWaveletCoefficients(k) 6 a' := 07 c := 08 <u>for</u> x := 0, ..., k - 1 <u>do</u> 9  $a' := a' + a_{x} w(x)$ 10  $c' := c' + a_{x} (-1)^{x} w(k - 1 - x)$ 11 <u>od</u> 12 <u>return</u> (a', c')

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Image Analysis / 2. Daubechies Wavelets

#### Daubechies Wavelets / Inverse DWT Algorithm

As  $D_k$  is orthogonal, one can easily compute the inverse of the DWT via:

$$\begin{pmatrix} a_0^{s+1} \\ a_1^{s+1} \\ a_2^{s+1} \\ \vdots \\ a_{n-1}^{s+1} \\ \vdots \\ a_{2n-1}^{s+1} \end{pmatrix} = \begin{pmatrix} w_0 & w_1 & w_3 & \dots & w_{k-1} \\ w_{k-1} & -w_{k-2} & w_3 & \dots & -w_0 \\ & w_0 & w_1 & \dots & w_{k-1} \\ & & w_{k-1} & -w_{k-2} & \dots & -w_0 \\ & & & \ddots & & & \\ w_2 & \dots & w_{k-1} & & & w_0 & w_1 \\ w_2 & \dots & -w_{k-1} & & & w_0 & -w_1 \end{pmatrix}^T \begin{pmatrix} a_0^s \\ c_0^s \\ a_1^s \\ c_1^s \\ \vdots \\ a_{n-1}^s \\ c_{n-1}^s \end{pmatrix}$$

#### Daubechies Wavelets / Inverse DWT Algorithm



```
i idwt-daubechies(coefficients c = (c_{s,t})_{s=0,\dots,n-1;t=0,\dots,2^s-1}, a', k):
 2 w := (w(x))_{x=0,\dots,k-1} := \text{getDaubechiesWaveletCoefficients}(k)
 3 a := (a_{s,t})_{s=0,\dots,n;\ t=0,\dots,2^s-1} := 0
 4 a_{0,0} := a'
 5 \text{ for } s := 0, \dots, n-1 \text{ do}
        for t := 0, \ldots, 2^s - 1 do
 6
             for x := 0, ..., k - 1 do
 7
                  a_{s+1,2t+x \mod 2^{s+1}} := a_{s+1,2t+x \mod 2^{s+1}} + a_{s,t+x \mod 2^s} w(x)
 8
                  a_{s+1,2t+1+x \mod 2^{s+1}} := a_{s+1,2t+1+x \mod 2^{s+1}} + c_{s,t+x \mod 2^s} (-1)^x w(k-1-x)
 9
10
             od
        od
11
12 od
13 f := (f(x))_{x=0,\dots,2^n-1} := a_{n,x}, \quad x = 0,\dots,2^n - 1
14 retu<u>rn</u> f
```

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Image Analysis / 2. Daubechies Wavelets

Silversitär 2003

Daubechies Wavelets / Daubechies Wavelet Basis Functions

Daubechies wavelets have been defined implicitely by their wavelet coefficients in the DWT.

But how does a Daubechies wavelet look like?

We run a unit vector of length 1024 through IDWT, i.e., we set all but one coefficient to zero.

Daubechies Wavelets /  $D_4$  Wavelet Basis Function (s = 8, t = 3)





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Daubechies Wavelets /  $D_{20}$  Wavelet Basis Function (s = 6, t = 3)



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- 1. Haar Wavelets
- 2. Daubechies Wavelets
- **3. Two-dimensional Wavelets**

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Image Analysis / 3. Two-dimensional Wavelets



etsitär .

 $\mathsf{haar}^b: \mathbb{R} \times \mathbb{R} \to \mathbb{R}, \quad b \in \{1, 2, 3\}$ 





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#### **Two-dimensional Haar Basis Functions**

The scaled and translated mother wavelets form a family of two-dimensional Haar basis functions:

$$\psi^b_{s,t_x,t_y}(x) := 2^s \cdot \mathsf{haar}^b(2^s x - t_x, 2^s y - t_y), \quad b \in \{1, 2, 3\}$$



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Image Analysis / 3. Two-dimensional Wavelets

# Orthogonality of Haar Basis Functions



$$\psi^b_{s,t_x,t_y}$$
 and  $\psi^{b'}_{s',t'_x,t'_y}$ 

with  $s, t_x, t_y, s', t'_x, t'_y \in \mathbb{Z}$ ,  $b, b' \in \{1, 2, 3\}$  are orthogonal:

$$\langle \psi^{b}_{s,t_{x},t_{y}}, \psi^{b'}_{s',t'_{x},t'_{y}} \rangle := \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \psi^{b}_{s,t_{x},t_{y}}(x) \cdot \psi^{b'}_{s',t'_{x},t'_{y}}(x) \, dx \, dy = 0$$

And

$$\langle \psi^b_{s,t_x,t_y}, \psi^b_{s,t_x,t_y} \rangle = 1$$

Proof. Analogously to the one-dimensional case.





#### 2D Haar Wavelets / Discrete Wavelet Transform

John Persitär Alideshey

A finite discrete signal f of size  $2^n \times 2^n$  can be represented by a finite sum of 2-dimensional Haar wavelets:

$$f(x) = a_{-n,0,0} + \sum_{b=1}^{3} \sum_{s=-n}^{-1} \sum_{t_x=0}^{2^{n+s}-1} \sum_{t_y=0}^{2^{n+s}-1} c_{s,t_x,t_y}^b \cdot 2^s \operatorname{haar}^b(2^s x - t_x, 2^s y - t_y)$$

The initial *a* values are just the signal values:

$$a_{s=0,t_x,t_y} := \int_{2^{-s}t_x}^{2^{-s}(t_x+1)} \int_{2^{-s}t_y}^{2^{-s}(t_y+1)} f(x,y) \, dx \, dy$$
$$= \int_{t_x}^{t_x+1} \int_{t_y}^{t_y+1} f(x,y) \, dx \, dy$$
$$= \sum_{x=t_x}^{$$

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Image Analysis / 3. Two-dimensional Wavelets

#### 2D Haar Wavelets / Computing Coefficients



The values of integrals with a simple rectangle impulse on different scales can be computed recursively:

$$\begin{aligned} a_{s,t_x,t_y} &:= 2^s \int_{2^{-s} t_x}^{2^{-s} (t_x+1)} \int_{2^{-s} t_y}^{2^{-s} (t_y+1)} f(x,y) \, dx dy \\ a_{s,t_x,t_y} &= \frac{1}{2} \left( a_{s+1,2t_x,2t_y} + a_{s+1,2t_x+1,2t_y} + a_{s+1,2t_x,2t_y+1} + a_{s+1,2t_x+1,2t_y+1} \right) \end{aligned}$$

The coefficients of the Haar wavelet can be computed from these values via

$$c_{s,t_x,t_y}^1 = \frac{1}{2} \left( a_{s+1,2t_x,2t_y} + a_{s+1,2t_x,2t_y+1} - a_{s+1,2t_x+1,2t_y} - a_{s+1,2t_x+1,2t_y+1} \right)$$
  

$$c_{s,t_x,t_y}^2 = \frac{1}{2} \left( a_{s+1,2t_x,2t_y} + a_{s+1,2t_x+1,2t_y} - a_{s+1,2t_x,2t_y+1} - a_{s+1,2t_x+1,2t_y+1} \right)$$
  

$$c_{s,t_x,t_y}^1 = \frac{1}{2} \left( a_{s+1,2t_x,2t_y} + a_{s+1,2t_x+1,2t_y+1} - a_{s+1,2t_x,2t_y+1} - a_{s+1,2t_x+1,2t_y} \right)$$

## Haar Wavelets / Computing Coefficients



1 dwt2d-haar(image  $f = (f(x, y))_{x=0,\dots,2^n-1,y=0,\dots,2^n-1}$ ): 2  $c := (c_{s,t_x,t_y}^b)_{s=0,\dots,n-1;\ t_x=0,\dots,2^s-1;\ t_y=0,\dots,2^s-1;\ b\in\{1,2,3\}} := 0$ 3  $a := (a_{s,t_x,t_y})_{s=0,\dots,n; t_x=0,\dots,2^s-1; t_y=0,\dots,2^s-1} := 0$ 4  $a_{n,t_x,t_y} := f(t_x, t_y), \quad t_x = 0, \dots, 2^n - 1, t_y = 0, \dots, 2^n - 1$  $5 \text{ <u>for</u>} s := n - 1, \dots, 0 \text{ <u>do</u>}$ for  $t_x := 0, \ldots, 2^s - 1$  do 6 for  $t_u := 0, \ldots, 2^s - 1$  do 7  $a_{s,t_x,t_y} := (a_{s+1,2t_x,2t_y} + a_{s+1,2t_x+1,2t_y} + a_{s+1,2t_x,2t_y+1} + a_{s+1,2t_x+1,2t_y+1})/2$ 8  $c_{s,t_x,t_y}^1 := (a_{s+1,2t_x,2t_y} + a_{s+1,2t_x,2t_y+1} - a_{s+1,2t_x+1,2t_y} - a_{s+1,2t_x+1,2t_y+1})/2$ 9  $\begin{aligned} s_{s,t_x,t_y}^{3,x_x,t_y} &:= (a_{s+1,2t_x,2t_y} + a_{s+1,2t_x+1,2t_y} - a_{s+1,2t_x,2t_y+1} - a_{s+1,2t_x+1,2t_y+1})/2 \\ c_{s,t_x,t_y}^3 &:= (a_{s+1,2t_x,2t_y} + a_{s+1,2t_x+1,2t_y+1} - a_{s+1,2t_x,2t_y+1} - a_{s+1,2t_x+1,2t_y})/2 \end{aligned}$ 10 11 od 12 od 13 14 **od** 15 **<u>return</u>**  $(a_{0,0,0}, c)$ 

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#### Image Analysis / 3. Two-dimensional Wavelets



# **Displaying 2D DWTs**



# Displaying 2D DWTs



rsitär

2003



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#### Image Analysis / 3. Two-dimensional Wavelets





Example







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#### Image Analysis / 3. Two-dimensional Wavelets



Example





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# Another Example







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Image Analysis / 3. Two-dimensional Wavelets



Separable 2D Wavelets Bases / Scaling Function

Many 2D wavelet bases can be constructed from 1D wavelet bases and a suitable scaling function  $\phi$  (also called father wavelet).

For the Haar wavelets the scaling function is just the rectangle impulse:

$$\phi(x) := \begin{cases} 1, \text{ if } x \in [0,1) \\ 0, \text{ else} \end{cases}$$

In the same manner as for the wavelet functions, one defines scaled and translated variants:

$$\phi_{s,t}(x) := 2^s \phi(2^s x - t)$$

#### Separable 2D Wavelets Bases / 2D Haar Basis



Obviously, the Haar basis wavelets can be constructed via

$$\psi^{1}(x, y) = \psi(x) \phi(y)$$
  

$$\psi^{2}(x, y) = \phi(x) \psi(y)$$
  

$$\psi^{3}(x, y) = \psi(x) \psi(y)$$

and

$$\phi(x,y) = \phi(x) \, \phi(y)$$

is a suitable 2D scaling function.

Separable wavelet bases allow a generic DWT that

1. applies a 1D DWT to each row of the image and then

2. applies another 1D DWT to each column of the result.

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Image Analysis / 3. Two-dimensional Wavelets

# Generic DWT Algorithm



1 dwt2d-generic(image  $f = (f(x, y))_{x=0,\dots,2^n-1,y=0,\dots,2^n-1}$ , wavelet transform W): 2  $c := (c_{s,t_x,t_y}^{\tilde{b}})_{s=0,\dots,n-1;\ t_x=0,\dots,2^s-1;\ t_y=0,\dots,2^s-1;\ b\in\{1,2,3\}} := 0$ 3  $a := (a_{s,t_x,t_y})_{s=0,\dots,n; t_x=0,\dots,2^s-1; t_y=0,\dots,2^s-1} := 0$ 4  $a_{n,t_x,t_y} := f(t_x,t_y), \quad t_x = 0,\dots,2^n - 1, t_y = 0,\dots,2^n - 1$ 5 for  $s := n - 1, \ldots, 0$  do  $a' := (a'_{t_x,t_y})_{t_x=0,\dots,2^{s+1}-1; t_y=0,\dots,2^s-1} := 0$ 6  $c' := (c'_{t_x, t_y})_{t_x = 0, \dots, 2^{s+1} - 1; t_y = 0, \dots, 2^s - 1} := 0$ 7 <u>for</u>  $t_x := 0, \ldots, 2^{s+1} - 1$  <u>do</u> 8  $(a'_{t_{x,\cdot}}, c'_{t_{x,\cdot}}) :=$ dwt-iteration $(a_{s+1,t_{x,\cdot}}, W)$ 9 od 10 <u>**for**</u>  $t_y := 0, \ldots, 2^s - 1$  <u>**do**</u> 12 13 14 od 15 16 **od** 17 **<u>return</u>**  $(a_{0,0,0}, c)$