

# Image Analysis

## 4. Wavelets

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Image Analysis



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

## **Basis Functions**

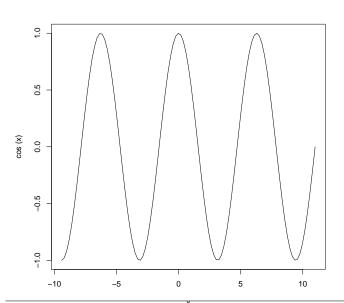


## Fourier Analysis:

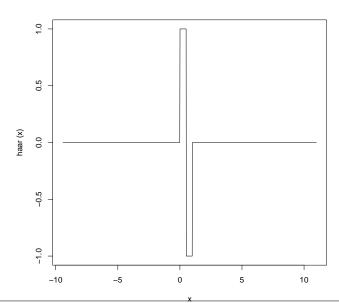
## Wavelets:

$$\psi(x) := \cos x$$

$$\psi(x) := \mathsf{haar}(x) := \left\{ \begin{array}{l} 1, \ x \in [0, \frac{1}{2}) \\ -1, \ x \in [\frac{1}{2}, 1) \\ 0, \ \mathsf{else} \end{array} \right.$$



 $\psi_{\omega}(x) := \cos 2\pi \omega x$ 



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## Image Analysis / 1. Haar Wavelets



#### **Basis Functions**

# Fourier Analysis:

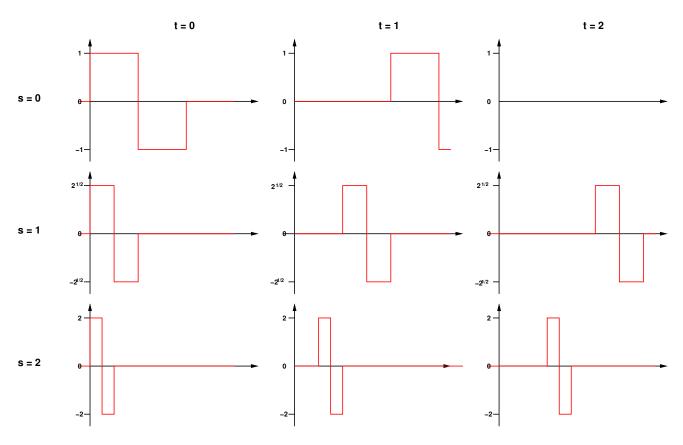
## Wavelets:

 $\psi_{s,t}(x) := \sqrt{2^s} \cdot \mathsf{haar}(2^s x - t)$ 

$$=\sqrt{2^{s}}\cdot \begin{cases} 1, \ x\in (2^{-s}\,t,2^{-s}\,(t+\frac{1}{2}))\\ -1, \ x\in [2^{-s}\,(t+\frac{1}{2}),2^{-s}\,(t+1))\\ 0, \ \text{else} \end{cases}$$

#### **Basis Functions**





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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



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

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

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



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:

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

# Haar Wavelets / Computing Coefficients / Example



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	_	_	_	_	_	_	_
$c_{-3}$	2.47	_	_	_	_	_	_	_

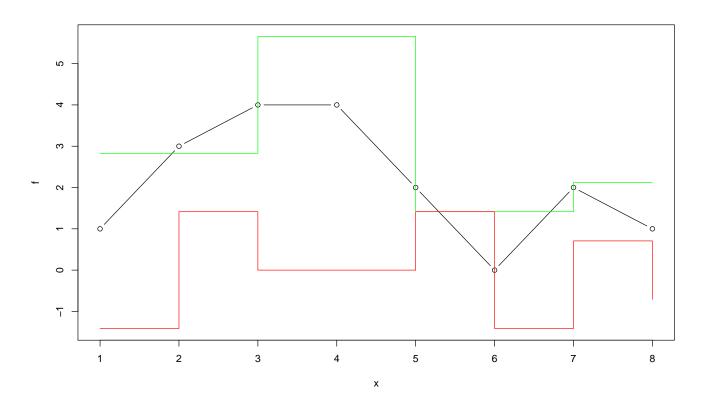
$$\mathsf{DWT}_{\mathsf{haar}}(f) = (6.01, 2.47, -2, -0.5, -1.41, 0.00, 1.41, 0.71)$$

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#### Image Analysis / 1. Haar Wavelets

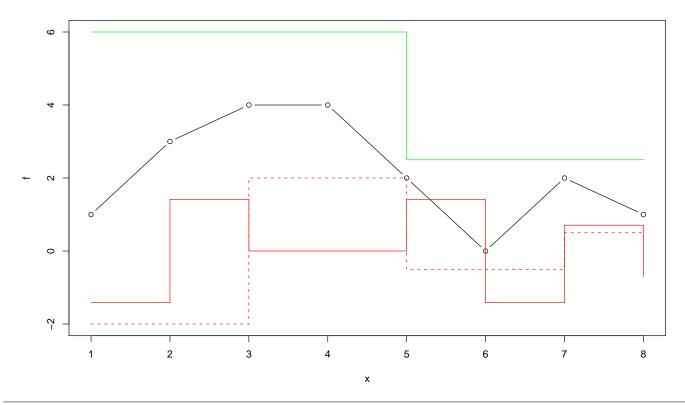
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# Haar Wavelets / Computing Coefficients / Example



# Haar Wavelets / Computing Coefficients / Example



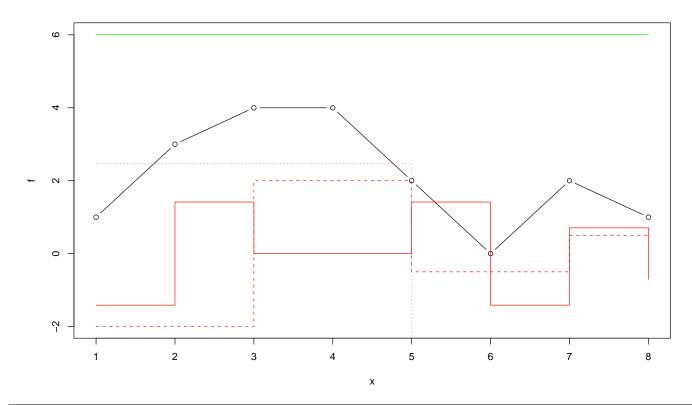


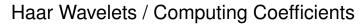
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#### Image Analysis / 1. Haar Wavelets

# Haar Wavelets / Computing Coefficients / Example









```
1 dwt-haar(sequence f=(f(x))_{x=0,\dots,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 for s:=n-1,\dots,0 do
6 for t:=0,\dots,2^s-1 do
7 a_{s,t}:=(a_{s+1,2t}+a_{s+1,2t+1})/\sqrt{2}
8 c_{s,t}:=(a_{s+1,2t}-a_{s+1,2t+1})/\sqrt{2}
9 od
10 od
11 return (a_{0,0},c)
```

#### 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

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





```
1 idwt-haar(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 for s:=0,\dots,n-1 do
5 for t:=0,\dots,2^s-1 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 od
9 od
10 f:=(f(x))_{x=0,\dots,2^n-1}:=a_{n,x}, \quad x=0,\dots,2^n-1
11 return f
```

#### 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:

$$w(D_2) = (\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}})$$

$$w(D_4) = (\frac{1+\sqrt{3}}{4\sqrt{2}}, \frac{3+\sqrt{3}}{4\sqrt{2}}, \frac{3-\sqrt{3}}{4\sqrt{2}}, \frac{1-\sqrt{3}}{4\sqrt{2}})$$

 $D_2$  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.





```
1 dwt-daubechies (sequence f = (f(x))_{x=0,\dots,2^n-1}, k):
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
a := (a_{s,t})_{s=0,\dots,n;\ t=0,\dots,2^s-1} := 0
s \ a_{n,t} := f(t), \quad t = 0, \dots, 2^n - 1
 6 for s := n - 1, \dots, 0 do
        for t := 0, \dots, 2^s - 1 do
            a_{s,t} := 0
            c_{s,t} := 0
            for x := 0, ..., k-1 do
                 a_{s,t} := a_{s,t} + a_{s+1,2t+x \bmod 2^{s+1}} w(x)
11
                 c_{s,t} := c_{s,t} + a_{s+1,2t+x \bmod 2^{s+1}} (-1)^x w(k-1-x)
12
13
             od
14
        od
15 od
16 return (a_{0,0},c)
```

### Image Analysis / 2. Daubechies Wavelets



## Generic DWT Algorithm (1/2)

```
\begin{array}{l} \text{$l$ dwt-generic}(\text{sequence }f=(f(x))_{x=0,\dots,2^n-1},\text{wavelet transform }W):$\\ 2\ c:=(c_{s,t})_{s=0,\dots,n-1;\ t=0,\dots,2^s-1}:=0\\ 3\ a:=(a_{s,t})_{s=0,\dots,n;\ t=0,\dots,2^s-1}:=0\\ 4\ a_{n,t}:=f(t),\quad t=0,\dots,2^n-1\\ 5\ \underline{\textbf{for}}\ s:=n-1,\dots,0\ \underline{\textbf{do}}\\ 6\ (c_{s,\cdot},a_{s,\cdot}):=\text{dwt-iteration}(a_{s+1,\cdot},W)\\ 7\ \underline{\textbf{od}}\\ 8\ \underline{\textbf{return}}\ (a_{0,0},c)\\ 9\\ 10\ d\text{wt-iteration}(\text{sequence }f=(f(x))_{x=0,\dots,2^{n+1}-1},\text{wavelet transform }W):$\\ 11\ a:=(a_t)_{t=0,\dots,2^n-1}:=0\\ 12\ c:=(c_t)_{t=0,\dots,2^n-1}:=0\\ 13\ \underline{\textbf{for}}\ t:=0,\dots,2^n-1\ \underline{\textbf{do}}\\ 14\ (a_t,c_t):=W((f_{2t+x\ \text{mod}\ 2^{n+1}})_{x=0,\dots,2^{n+1}-1})\\ 15\ \underline{\textbf{od}}\\ 16\ \textbf{return}\ (c,a)\\ \end{array}
```

## Generic DWT Algorithm (2/2)



```
## W-haar(sequence a = (a(t))_{t=0,...,2^n-1}):

## Preference of the proof of the content of
```

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### Image Analysis / 2. Daubechies Wavelets

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# Daubechies Wavelets / Inverse DWT Algorithm

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

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





```
1 idwt-daubechies (coefficients c = (c_{s,t})_{s=0,\dots,n-1;\ t=0,\dots,2^s-1}, a', k):
 w := (w(x))_{x=0,\dots,k-1} := \text{getDaubechiesWaveletCoefficients}(k)
 a := (a_{s,t})_{s=0,\dots,n;\ t=0,\dots,2^s-1} := 0
 a_{0,0} := a'
 s \ \mathbf{for} \ s := 0, \dots, n-1 \ \mathbf{do}
        for t := 0, \dots, 2^s - 1 do
             for x := 0, ..., k - 1 do
                  a_{s+1,2t+x \bmod 2^{s+1}} := a_{s+1,2t+x \bmod 2^{s+1}} + a_{s,t+x \bmod 2^s} w(x)
                  a_{s+1,2t+1+x \bmod 2^{s+1}} := a_{s+1,2t+1+x \bmod 2^{s+1}} + c_{s,t+x \bmod 2^{s}} (-1)^{x} w(k-1-x)
10
             <u>od</u>
        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 return f
```

### Image Analysis / 2. Daubechies Wavelets



Daubechies Wavelets / Daubechies Wavelet Basis Functions

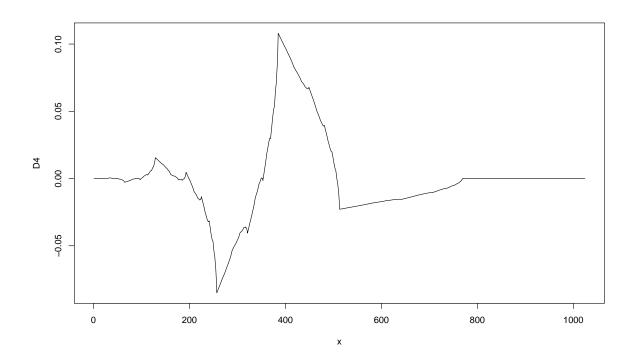
Daubechies wavelets have been defined implicitely by their wavelet coefficients in the DWT.

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.

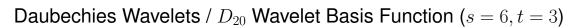
# Daubechies Wavelets / $D_4$ Wavelet Basis Function (s=8,t=3)



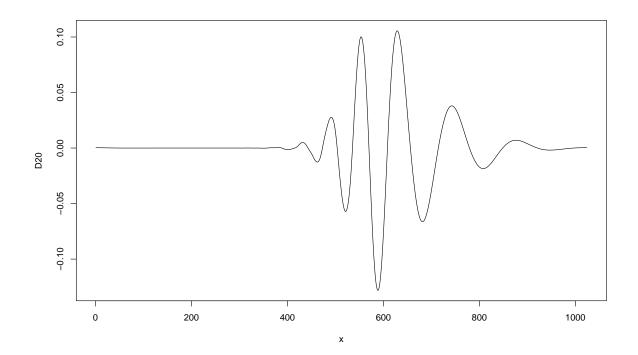


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#### Image Analysis / 2. Daubechies Wavelets









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

## Image Analysis / 3. Two-dimensional Wavelets

## Two-dimensional Haar Mother Wavelets



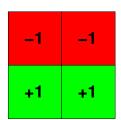
$$\mathsf{haar}^b: \mathbb{R} \times \mathbb{R} \to \mathbb{R}, \quad b \in \{1, 2, 3\}$$

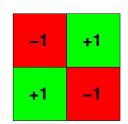
$$\begin{array}{l} \mathsf{haar}^1(x,y) := \\ \begin{cases} +1, \ \mathsf{if} \ x \in [0,\frac{1}{2}) \\ -1, \ \mathsf{if} \ x \in [\frac{1}{2},1) \\ 0, \ \mathsf{else} \end{cases} \end{array}$$

$$\begin{cases} \mathsf{haar}^2(x,y) := \\ +1, \ \text{if} \ y \in [0,\frac{1}{2}) \\ -1, \ \text{if} \ y \in [\frac{1}{2},1) \\ 0, \ \text{else} \end{cases}$$

$$\begin{array}{l} \mathsf{haar}^2(x,y) := \\ \begin{cases} +1, \ \mathsf{if} \ y \in [0,\frac{1}{2}) \\ -1, \ \mathsf{if} \ y \in [\frac{1}{2},1) \\ 0, \ \mathsf{else} \end{cases} & \begin{array}{l} \mathsf{haar}^3(x,y) := \\ +1, \ \mathsf{if} \ (x,y) \ \in [0,\frac{1}{2})^2 \\ \cup [\frac{1}{2},1)^2 \\ -1, \ \mathsf{if} \ (x,y) \ \in [0,\frac{1}{2}) \times [\frac{1}{2},1 \\ \cup [\frac{1}{2},1) \times [0,\frac{1}{2}) \end{array} \end{array}$$





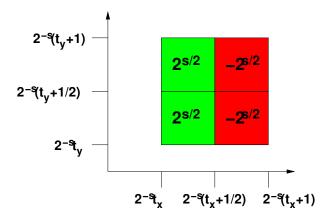


#### Two-dimensional Haar Basis Functions



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

Obviously, two distinct 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

$$\langle \psi_{s,t_x,t_y}^b, \psi_{s,t_x,t_y}^b \rangle = 1$$

Proof. Analogously to the one-dimensional case.

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



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



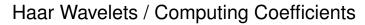
The values of integrals with a simple rectangle impulse on different scales can be computed recursively:

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

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

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

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



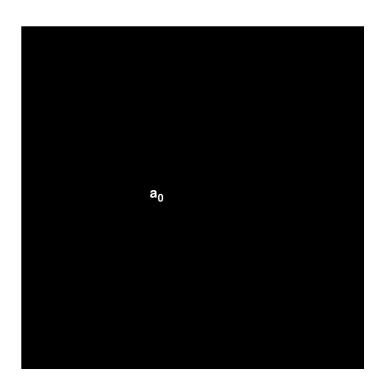


```
1 dwt2d-haar(image f = (f(x,y))_{x=0,...,2^n-1,y=0,...,2^n-1}):
 2 c := (c_{s,t_x,t_y}^b)_{s=0,\dots,n-1;\ t_x=0,\dots,2^s-1;\ t_y=0,\dots,2^s-1;\ b\in\{1,2,3\}} := 0
 a := (a_{s,t_x,t_y})_{s=0,\dots,n;\ t_x=0,\dots,2^s-1;\ t_y=0,\dots,2^s-1} := 0
4 a_{n,t_x,t_y} := f(t_x, t_y), \quad t_x = 0, \dots, 2^n - 1, t_y = 0, \dots, 2^n - 1
 s \ \underline{\mathbf{for}} \ s := n - 1, \dots, 0 \ \underline{\mathbf{do}}
          for t_x := 0, \dots, 2^s - 1 do
                 for t_y := 0, \dots, 2^s - 1 do
                       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
                       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
                       c_{s,t_x,t_y}^2 := (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
10
11
12
          od
13
14 od
15 return (a_{0,0,0},c)
```

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

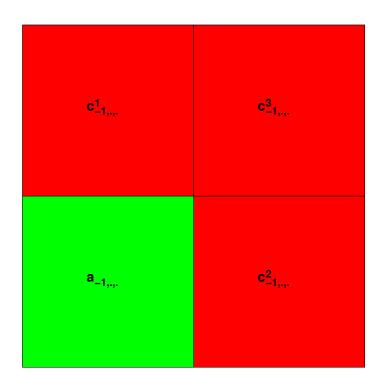
# ersität jildeshein

## Displaying 2D DWTs



# Displaying 2D DWTs



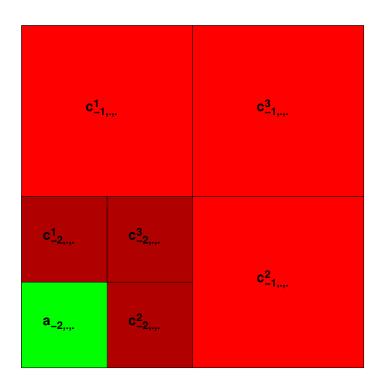


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### Image Analysis / 3. Two-dimensional Wavelets

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# Displaying 2D DWTs



# Example







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## Image Analysis / 3. Two-dimensional Wavelets

# Example





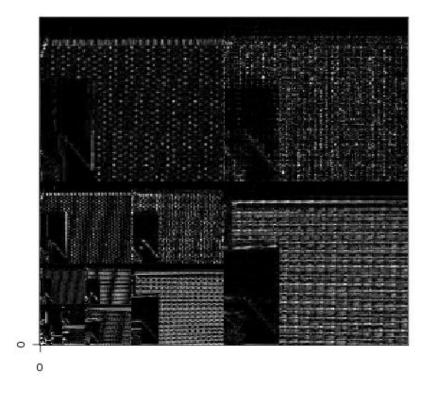


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## Another Example







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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:

$$\phi(x) := \left\{ \begin{array}{l} 1, \text{ if } x \in [0,1) \\ 0, \text{ else} \end{array} \right.$$

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

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## 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
 s for s := n - 1, \dots, 0 do
            a' := (a'_{t_r,t_u})_{t_x=0,\dots,2^{s+1}-1;\ t_u=0,\dots,2^s-1} := 0
            c' := (c'_{t_x,t_y})_{t_x=0,\dots,2^{s+1}-1;\ t_y=0,\dots,2^s-1} := 0
            for t_x := 0, \dots, 2^{s+1} - 1 do
                   (a'_{t_x,.},c'_{t_x,.}) := \operatorname{dwt-iteration}(a_{s+1,t_x,.},W)
10
            <u>for</u> t_y := 0, \dots, 2^s - 1 <u>do</u>
12
                    \begin{array}{l} (a_{s,.,t_y},c_{s,.,t_y}^2) := \operatorname{dwt-iteration}(a'_{.,t_y},W) \\ (c_{s,.,t_y}^1,c_{s,.,t_y}^3) := \operatorname{dwt-iteration}(c'_{.,t_y},W) \end{array} 
13
14
15
16 od
17 return (a_{0,0,0},c)
```