

Continuous wavelet transform (CWT) and edge detection

WTBV WS 2014/15

January 23, 2015

- 1 Continuous wavelet transform (CWT)
- 2 Edges and wavelet coefficients
- 3 Discrete approximation of the CWT in MRA context
- 4 The à-trous scheme
- 5 2-dimensional separable CWT
- 6 Edges in images

- Initial event:
A. GROSSMANN and J. MORLET,
Decompositions of Hardy functions into square integrable wavelets of constant shape, *SIAM J. Math. Analysis*, 1984
(Analysis of seismic signals)
- ... but there were precursors ... e.g.
A. P. CALDÉRON,
Intermediate Spaces and Interpolation, the Complex Method,
Studia Mathematica, 1964
- see:
S. JAFFARD, Y. MEYER, R. RYAN,
Wavelets, Tools for Science and Technology, SIAM 2001,
in particular: Chap. 2: Wavelets from a Historical Perspective

- Let $\psi : \mathbb{R} \rightarrow \mathbb{C}$ be a “suitable” wavelet function
- now: continuous dilation and translation of ψ

$$\psi_{s,a}(t) = \frac{1}{\sqrt{|s|}} \psi\left(\frac{t-a}{s}\right) \quad (s, a \in \mathbb{R})$$

- *continuous wavelet transform* (CWT) of a signal $f : \mathbb{R} \rightarrow \mathbb{C}$ using $\psi(t)$ defined as

$$f^\psi(s, a) = \langle f, \psi_{s,a} \rangle = \int_{\mathbb{R}} f(t) \overline{\psi_{s,a}(t)} dt = \sqrt{|s|} \int_{\mathbb{R}} f(st+a) \overline{\psi(t)} dt$$

- Intuitively: $f^\psi(s, a)$ represents the behavior of $f(t)$ in the vicinity of $a \in \mathbb{R}$ in resolution (scaling) $s \in \mathbb{R}$:

$$\|f(t) - \psi_{s,a}(t)\|^2 = \|f(t)\|^2 + \|\psi_{s,a}(t)\|^2 - 2 \Re \left[f^\psi(s, a) \right]$$

Only the \Re -term depends on s and a !

Minimizing $\|f(t) - \psi_{s,a}(t)\|^2$ means maximizing $\Re \dots$

- Let $\psi(t)$ be a wavelet function with $\|\psi\|^2 = 1$ (w.l.o.g.), then $t \mapsto |\psi(t)|^2$ can be viewed as a probability density on \mathbb{R} with average μ and variance σ^2 :

$$\mu = \int t |\psi(t)|^2 dt \quad \sigma^2 = \int (t - \mu)^2 |\psi(t)|^2 dt$$

- Parseval-Plancherel: $\|\widehat{\psi}\|^2 = \|\psi(t)\|^2 = 1$

Also $\lambda \mapsto |\widehat{\psi}(\lambda)|^2$ is a probability density with average $\widehat{\mu}$ and variance $\widehat{\sigma}^2$

$$\widehat{\mu} = \int \lambda |\widehat{\psi}(\lambda)|^2 d\lambda \quad \widehat{\sigma}^2 = \int (\lambda - \widehat{\mu})^2 |\widehat{\psi}(\lambda)|^2 d\lambda$$

- For $s > 0, a \in \mathbb{R}$ one has

$$\begin{aligned} \|\widehat{\psi_{s,a}}(t)\|^2 &= \|\psi_{s,a}(t)\|^2 = \|\psi(t)\|^2 = 1 \\ \widehat{\psi_{s,a}}(\lambda) &= \sqrt{s} e^{-2\pi i a \lambda} \widehat{\psi}(s\lambda) \end{aligned}$$

- Localization in the time domain

$$\mu_{s,a} = \int t |\psi_{s,a}(t)|^2 dt = \dots = s \mu + a$$

$$\sigma_{s,a}^2 = \int (t - \mu_{s,a})^2 |\psi_{s,a}|^2 dt = \dots = s^2 \sigma^2$$

- Localization in the frequency domain

$$\hat{\mu}_{s,a} = \int t |\widehat{\psi}_{s,a}(t)|^2 dt = \dots = \frac{1}{s} \hat{\mu}$$

$$\hat{\sigma}_{s,a}^2 = \int (t - \mu_{s,a})^2 |\widehat{\psi}_{s,a}|^2 dt = \dots = \frac{1}{s^2} \hat{\sigma}^2$$

- The “uncertainty” $\sigma_{s,a}^2 \cdot \hat{\sigma}_{s,a}^2$ is independent of s and a

$$\sigma_{s,a}^2 \cdot \hat{\sigma}_{s,a}^2 = \sigma^2 \cdot \hat{\sigma}^2$$

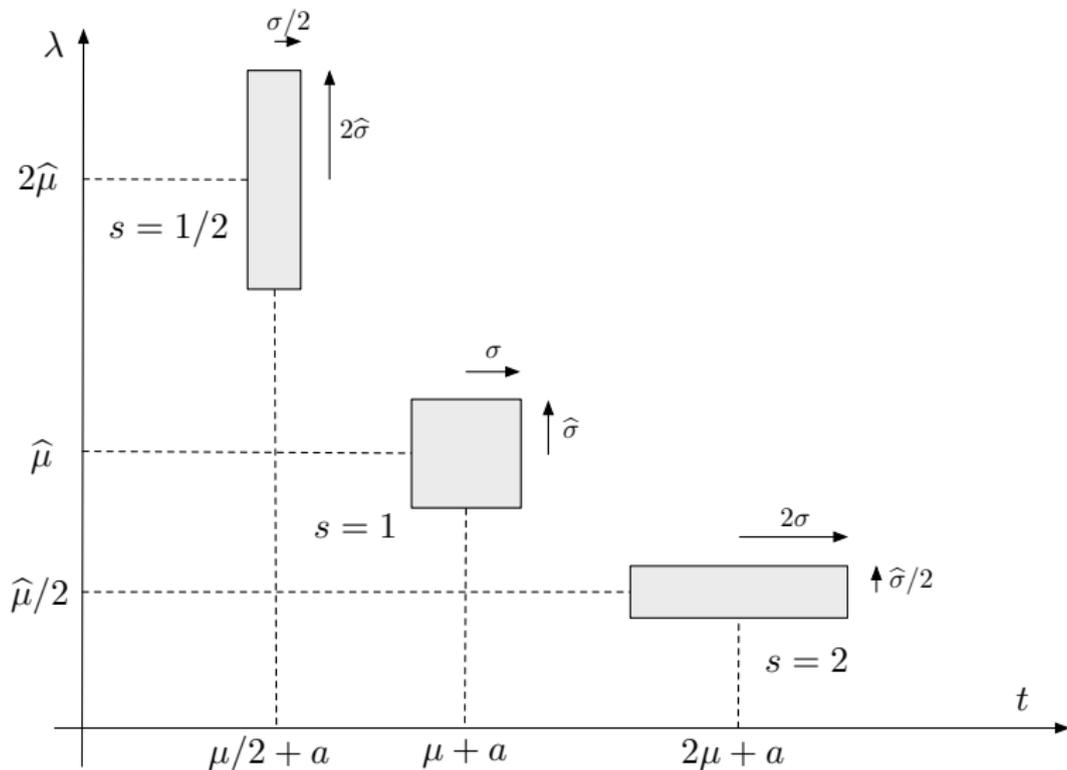


Figure: Heisenberg boxes for $\psi_{s,a}$, $s = 1/2, 1, 2$

- HAAR wavelet function

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

- *mexican-hat* wavelet

$$\psi_{mex}(t) = (1 - 2t^2) e^{-t^2}$$

- MORLET wavelet

$$\psi_{mor}(t) = e^{-t^2} \cos\left(\pi\sqrt{\frac{2}{\ln 2}}t\right)$$

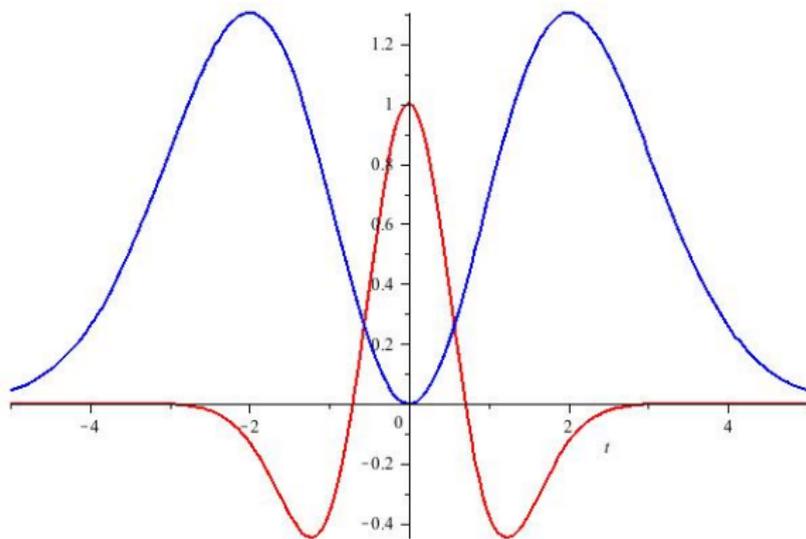


Figure: mexican-hat wavelet (in red) and its spectrum (in blue)

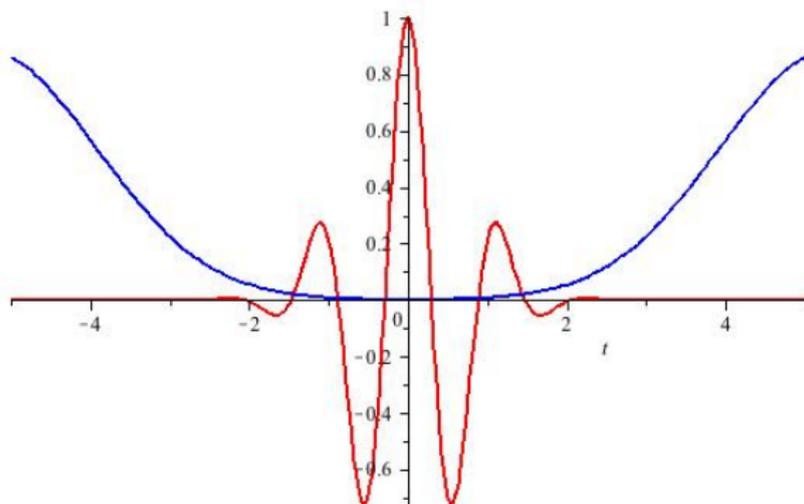


Figure: MORLET wavelet (in red and its spectrum (in blue))

- Fourier transforms

$$\widehat{f}_{haar}(s) = \frac{4i(\sin(1/4s))^2 e^{-1/2is}}{s} \quad \widehat{f}_{haar}(0) = 0$$

$$\widehat{f}_{mex}(s) = 1/2 s^2 e^{-1/4s^2} \sqrt{\pi} \quad \widehat{f}_{mex}(0) = 0$$

$$\widehat{f}_{mor}(s) = \sqrt{\pi} \cosh\left(1/2 \frac{s\pi\sqrt{2}}{\sqrt{\ln(2)}}\right) e^{-1/4s^2 - 1/2 \frac{\pi^2}{\ln(2)}} \quad \widehat{f}_{mor}(0) \approx 0.0014$$

- admissibility* constants

$$C_{haar} = \int_{s=-\infty}^{\infty} \frac{|\widehat{f}_{haar}(s)|^2}{|s|} ds = 2 \ln(2)$$

$$C_{mex} = \int_{s=-\infty}^{\infty} \frac{|\widehat{f}_{mex}(s)|^2}{|s|} ds = \pi$$

$$C_{mor} = \int_{s=-\infty}^{\infty} \frac{|\widehat{f}_{mor}(s)|^2}{|s|} ds = \infty$$

- Intuitively:

$$f^\psi(s, a) = \int_{t=-\infty}^{\infty} f(t) \frac{1}{\sqrt{|s|}} \psi\left(\frac{t-a}{s}\right) dt$$

represents the behavior of $f(t)$ in the vicinity of $a \in \mathbb{R}$ in resolution (scaling) $s \in \mathbb{R}$

- The data

$$\left(f^\psi(s, a) \right)_{s>0, a \in \mathbb{R}}$$

give a highly redundant representation of the function $f(t)$

- Problem: how can one recover $f(t)$ from these data ?

- CALDÉRON's reconstruction formula:

$$f(t) = \frac{1}{C_\psi} \int_{s \in \mathbb{R}} \int_{a \in \mathbb{R}} f^\psi(s, a) \psi_{s,a}(t) da \frac{ds}{s^2}$$

where

$$0 < C_\psi = \int_{\lambda \in \mathbb{R}} \frac{|\widehat{\psi}(\lambda)|^2}{|\lambda|} d\lambda < \infty$$

- Note that the condition $C_\psi < \infty$ implies

$$\int_{\mathbb{R}} \psi(t) dt = \widehat{\psi}(0) = 0$$

- If $\psi : \mathbb{R} \rightarrow \mathbb{R}$ is a real wavelet function, then CALDÉRON's formula can be written as

$$f(t) = \frac{1}{C'_\psi} \int_{s>0} \int_{a \in \mathbb{R}} f^\psi(s, a) \psi_{s,a}(t) da \frac{ds}{s^2}$$

where

$$0 < C'_\psi = \int_{\lambda>0} \frac{|\widehat{\psi}(\lambda)|^2}{\lambda} d\lambda < \infty$$

- This simplification is justified by the symmetry property

$$\overline{\widehat{\psi}(\lambda)} = \widehat{\psi}(-\lambda)$$

for any real function $\psi(t)$

- Lemma (1) [Fourier transform w.r.t. t]

$$[\psi_{s,a}(t)]^{\wedge_t}(\lambda) = \sqrt{|s|} e^{-2\pi i a \lambda} \widehat{\psi}(\lambda s)$$

- Lemma (2) [Fourier transform w.r.t. a]

$$[\overline{\psi_{s,a}(t)}]^{\wedge_a}(\lambda) = \frac{s}{\sqrt{|s|}} e^{-2\pi i t \lambda} \overline{\widehat{\psi}(\lambda s)}$$

- Lemma (3) [Fourier transform w.r.t. a]

$$[f^\psi(s, a)]^{\wedge_a}(\lambda) = \frac{s}{\sqrt{|s|}} \widehat{f}(\lambda) \overline{\widehat{\psi}(\lambda s)}$$

- Consequence of Lemma (3):

$$\begin{aligned}
 f^\psi(s, a) &= \left[\frac{s}{\sqrt{|s|}} \widehat{f}(\lambda) \overline{\widehat{\psi}(\lambda s)} \right]_{\mathbb{R}}^{\vee_a} \\
 &= \frac{s}{\sqrt{|s|}} \int_{\mathbb{R}} \widehat{f}(\lambda) \overline{\widehat{\psi}(\lambda s)} e^{2\pi i a \lambda} d\lambda
 \end{aligned}$$

- This indicates an efficient way for computing the wavelet coefficients $f^\psi(s, a)$ based on the FFT:
 - 1 compute $\widehat{f}(\lambda)$
 - 2 compute $\widehat{\psi}(\lambda)$
(NB $\widehat{\psi}$ is explicitly known in many cases)
 - 3 multiply $\widehat{f}(\lambda) \cdot \overline{\widehat{\psi}(\lambda s)}$
 - 4 apply the inverse FFT

Proof (sketch) of CALDÉRON's reconstruction formula

- From Parseval-Plancherel and Lemmas (2) and (3) one gets

$$\begin{aligned}
 \int_{a \in \mathbb{R}} f^\psi(s, a) \psi_{s,a}(t) da &= \langle f^\psi(s, a), \overline{\psi_{s,a}(t)} \rangle_a = \\
 &= \langle [f^\psi(s, a)]^{\wedge a}(\lambda), [\overline{\psi_{s,a}(t)}]^{\wedge a}(\lambda) \rangle_\lambda \\
 &= \frac{s^2}{|s|} \cdot \langle \widehat{f}(\lambda) \overline{\widehat{\psi}(\lambda s)}, e^{-2\pi i t \lambda} \overline{\widehat{\psi}(\lambda s)} \rangle_\lambda \\
 &= \frac{s^2}{|s|} \cdot \int_{\lambda \in \mathbb{R}} \widehat{f}(\lambda) |\widehat{\psi}(\lambda s)|^2 e^{2\pi i t \lambda} d\lambda
 \end{aligned}$$

- and then

$$\begin{aligned}
 \int_{s \in \mathbb{R}} \int_{a \in \mathbb{R}} f^\psi(s, a) \psi_{s,a}(t) da \frac{ds}{s^2} &= \int_{\lambda \in \mathbb{R}} \hat{f}(\lambda) e^{2\pi i t \lambda} \int_s \frac{|\hat{\psi}(\lambda s)|^2}{|s|} ds d\lambda \\
 &= \int_{\lambda} \hat{f}(\lambda) e^{2\pi i t \lambda} \int_s \frac{|\hat{\psi}(s)|^2}{|s|} ds d\lambda \\
 &= C_\psi \cdot \int_{\lambda \in \mathbb{R}} \hat{f}(\lambda) e^{2\pi i t \lambda} d\lambda \\
 &= C_\psi \cdot f(t)
 \end{aligned}$$

- Theorem

- 1 If $\psi(t)$ is a continuous function with

$$\int_{t \in \mathbb{R}} \psi(t) dt = 0$$

- 2 and if there are positive constants A, B s.th.

$$|\psi(t)| \leq A e^{-B|t|} \quad (t \in \mathbb{R})$$

(exponentially rapid vanishing at infinity)

then

$$C_\psi = \int_{\lambda \in \mathbb{R}} \frac{|\widehat{\psi}(\lambda)|^2}{|\lambda|} d\lambda < \infty$$

and CALDÉRON's reconstruction formula holds for all $f \in \mathcal{L}^2(\mathbb{R})$

- Remarks on condition $C_\psi < \infty$

- Eponentially rapid vanishing of $\psi(t)$ at infinity implies $\psi(t) \in \mathcal{L}^2(\mathbb{R})$ and $\widehat{\psi}(\lambda) \in \mathcal{L}^2(\mathbb{R})$ and $\widehat{\psi}(\lambda) \in \mathcal{C}^1(\mathbb{R})$ (differentiability)
- Decompose the integral into two parts

$$C_\psi = \int_{\lambda \in \mathbb{R}} \frac{|\widehat{\psi}(\lambda)|^2}{|\lambda|} d\lambda = \int_{|\lambda| \leq 1} \dots + \int_{|\lambda| \geq 1} \dots$$

- Taylor expansion of $\widehat{\psi}(\lambda)$ at $\lambda = 0$ and

$$\widehat{\psi}(0) = \int \psi(t) dt = 0$$

shows that the first integral $\int_{|\lambda| \leq 1} \dots$ is finite

- As for the second integral,

$$\int_{|\lambda| \geq 1} \dots \leq \int |\widehat{\psi}(\lambda)|^2 d\lambda \leq \|\widehat{\psi}\|^2 < \infty$$

shows that this is finite too

- The HAAR wavelet function $\psi_{haar}(t)$ can be regarded as a derivative

$$\psi_{haar}(t) = \frac{d}{dt}\Delta(t) \quad \text{mit} \quad \Delta(t) = \begin{cases} t & 0 \leq t \leq 1/2 \\ 1 - t & 1/2 \leq t \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

- The mexican-hat wavelet function $\psi_{mex}(t)$ is a derivative

$$\psi_{mex}(t) = \frac{d}{dt} \left(t e^{-t^2} \right) = \frac{d^2}{dt^2} \frac{-e^{-t^2}}{2}$$

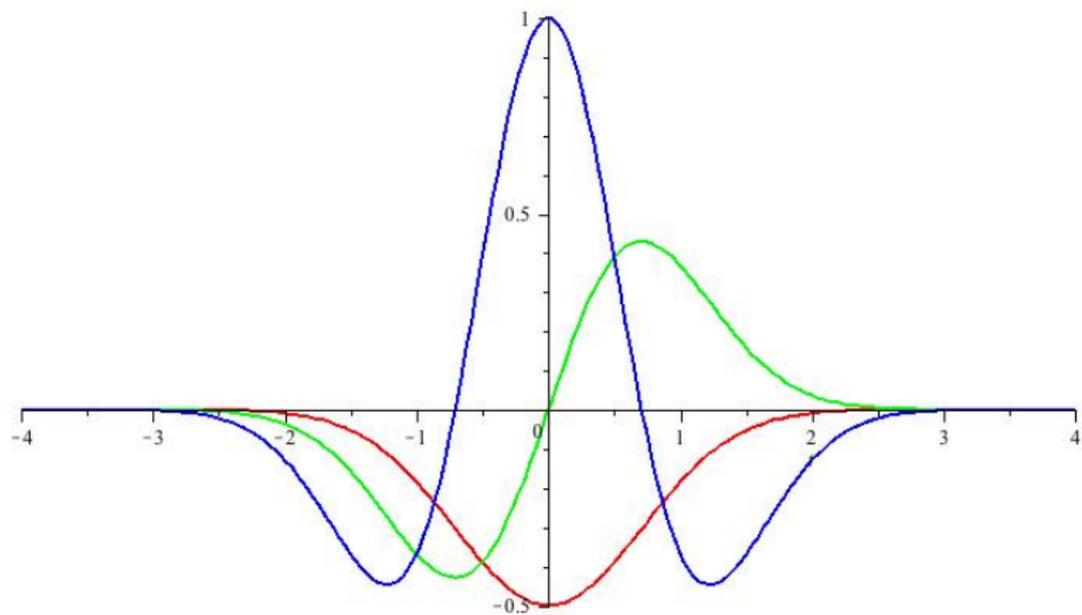


Figure: mexican-hat wavelet as second derivative of a Gaussian

- Let $\psi(t)$ be a wavelet function in the sense of the Theorem
- Let $\psi(t)$ be the derivative of a “smoothing function” $\theta(t)$

$$\psi(t) = \frac{d}{dt} \theta(t)$$

- Scaling of $\theta(t)$

$$\overleftarrow{\theta}_s(t) = \frac{1}{s} \theta\left(-\frac{t}{s}\right)$$

- Then

$$(*) \quad f^\psi(s, a) = -s^{-3/2} \frac{d}{da} (f \star \overleftarrow{\theta}_s)(a)$$

- Note: $f \star \overleftarrow{\theta}_s$ is a $\overleftarrow{\theta}_s$ -smoothed version of f

- Interpretation:

Edges in the graph of $f(t)$ can be recognized by absolutely large values of the wavelet coefficients $f^\psi(s, a)$ over many scales (s values)

- Proof of (*)

We have

$$(f \star \overleftarrow{\theta}_s)(a) = \int_{t \in \mathbb{R}} f(t) \overleftarrow{\theta}_s(a - t) dt = \int_{t \in \mathbb{R}} f(t) \frac{1}{s} \theta\left(\frac{t - a}{s}\right) dt$$

and hence

$$\begin{aligned} \frac{d}{da}(f \star \overleftarrow{\theta}_s)(a) &= \int_{t \in \mathbb{R}} f(t) \frac{1}{s} \theta'\left(\frac{t - a}{s}\right) \left(-\frac{1}{s}\right) dt \\ &= \int_{t \in \mathbb{R}} f(t) \left(-\frac{1}{s^2}\right) \psi\left(\frac{t - a}{s}\right) dt = -s^{-3/2} \langle f, \psi_{s,a} \rangle \end{aligned}$$

- Assume that the wavelet function $\psi(t)$ belongs to a MRA with scaling function $\phi(t)$
- Scaling and wavelet identities are

$$\phi(t) = \sqrt{2} \sum_{k \in \mathbb{Z}} h_k \phi(2t - k)$$

$$\psi(t) = \sqrt{2} \sum_{k \in \mathbb{Z}} g_k \phi(2t - k)$$

- Approximation and detail coefficients of a function $f(t)$, using dyadic scaling and integer translation $(s, a) = (2^m, n)$, are

$$a_{m,n} = \langle f, \phi_{2^m,n} \rangle \quad d_{m,n} = \langle f, \psi_{2^m,n} \rangle$$

- Recursion formulas

$$\phi_{2^{m+1},n}(t) = 2^{-(m+1)/2} \phi\left(\frac{t-n}{2^{m+1}}\right) = \dots = \sum_k h_k \phi_{2^m,n+k} 2^m(t)$$

$$\psi_{2^{m+1},n}(t) = 2^{-(m+1)/2} \psi\left(\frac{t-n}{2^{m+1}}\right) = \dots = \sum_k g_k \phi_{2^m,n+k} 2^m(t)$$

- Recursion formulas for approximation and wavelet coefficients

$$a_{m+1,n} = \sum_{k \in \mathbb{Z}} h_k a_{m,n+k} 2^m \quad (n \in \mathbb{Z})$$

$$d_{m+1,n} = \sum_{k \in \mathbb{Z}} g_k a_{m,n+k} 2^m \quad (n \in \mathbb{Z})$$

- Written as filtering operations

$$(a_{m+1,n})_{n \in \mathbb{Z}} = \overleftarrow{[(\uparrow_2)^m \mathbf{h}]} \star (a_{m,n})_{n \in \mathbb{Z}}$$

$$(d_{m+1,n})_{n \in \mathbb{Z}} = \overleftarrow{[(\uparrow_2)^m \mathbf{g}]} \star (a_{m,n})_{n \in \mathbb{Z}}$$

- Here $(\uparrow_2)^m \mathbf{h}$ is the filter constructed from \mathbf{h} by using m -fold upsampling with factor 2
- Algorithmic realization *algorithme à trous*
- M. HOLSCHNEIDER et al., A real-time algorithm for signal analysis with the help of wavelet transform. In: *Wavelets, Time-Frequency Methods and Phase Space*, Springer-Verlag, 1989

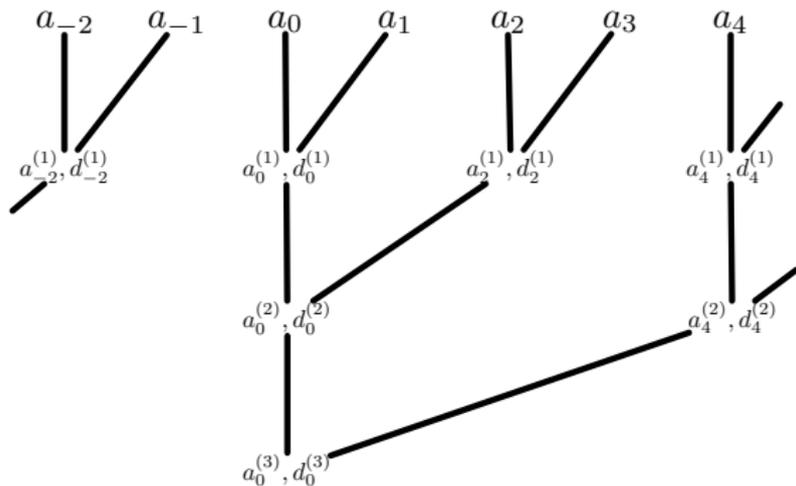


Figure: Scheme of the Haar transform

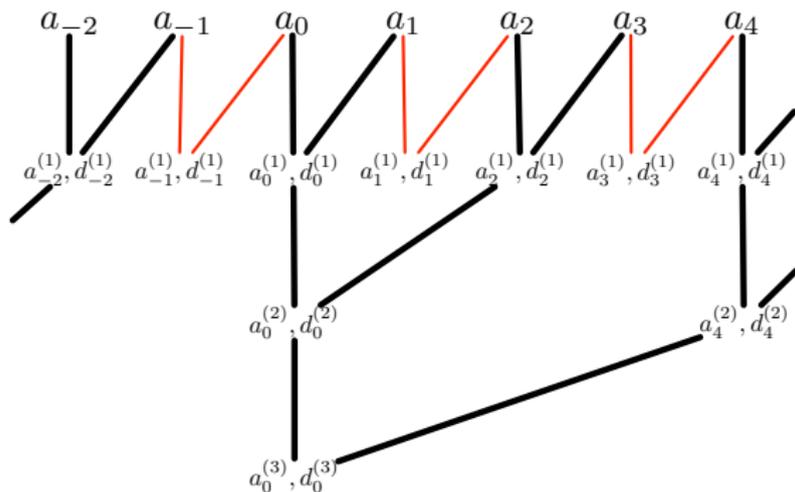


Figure: à-trous scheme (one level) for the Haar transform

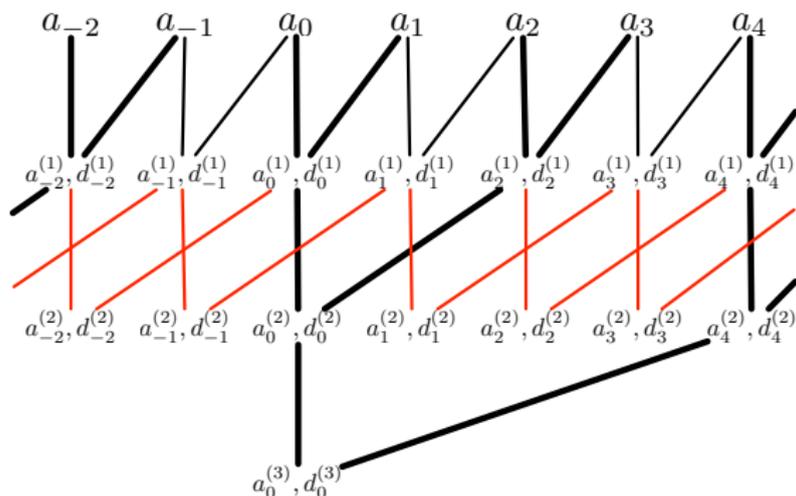


Figure: à-trous scheme (two levels) for the Haar transform

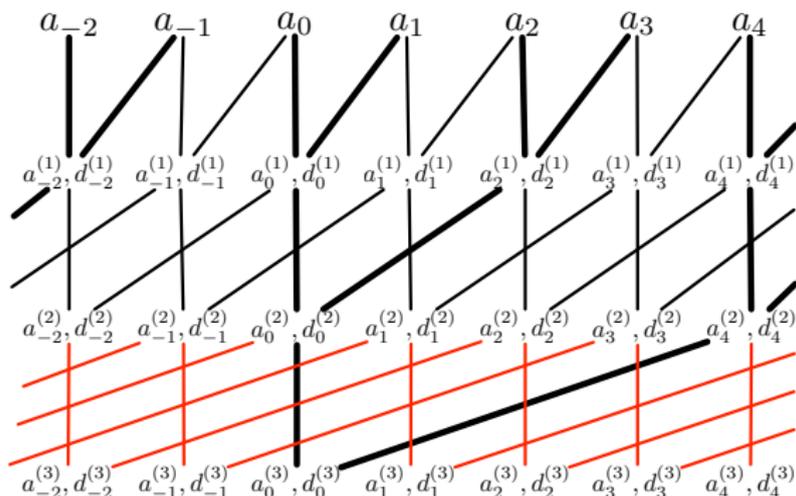


Figure: à-trous scheme (three levels) for the Haar transform

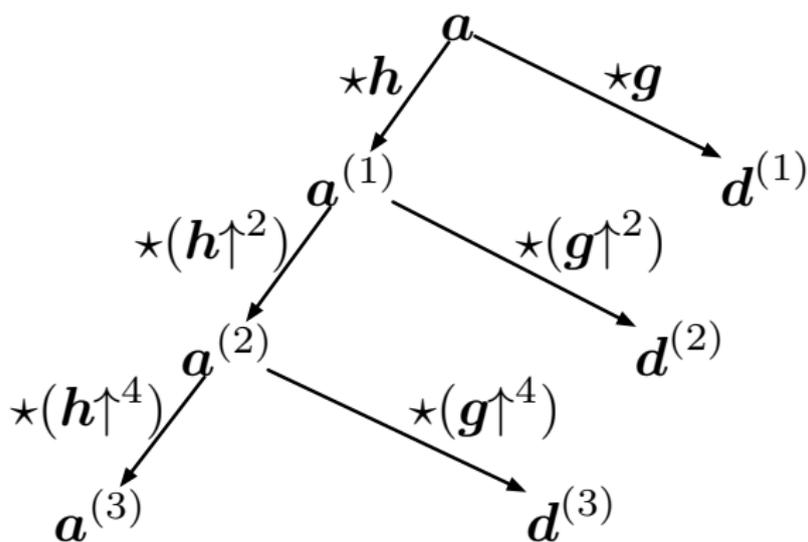


Figure: à-trous scheme (three levels)

high-pass filter: \mathbf{g} , low-pass filter: \mathbf{h} , signal: $\mathbf{a} = (a_k)_{n \in \mathbb{Z}}$

filtered signals: $\mathbf{a}^{(k)} = (a_n^{(k)})_{n \in \mathbb{Z}}$, $\mathbf{d}^{(k)} = (d_n^{(k)})_{n \in \mathbb{Z}}$,

- Let $\psi(x)$ be a one-dimension wavelet function
- $\Psi(x, y) = \psi(x) \psi(y)$ the two-dimensional separable wavelet function constructed from it
- The 2-dim. CWT of a function $f(x, y)$ is

$$f^\Psi(a, b, s) = \frac{1}{s} \iint_{x, y \in \mathbb{R} \times \mathbb{R}} f(x, y) \Psi\left(\frac{x-a}{s}, \frac{y-b}{s}\right) dx dy$$

- Let $\psi(x) = \frac{d}{dx} \theta(x)$ be the derivative of a “smoothing function” $\theta(x)$
- 2-dim separable smoothing function

$$\Theta(x, y) = \theta(x) \theta(y)$$

- 2-dim partial wavelet functions

$$\Psi^x(x, y) = \psi(x) \theta(y) = \frac{\partial}{\partial x} \Theta(x, y)$$

$$\Psi^y(x, y) = \theta(x) \psi(y) = \frac{\partial}{\partial y} \Theta(x, y)$$

- 2-dim partial CWT

$$\begin{aligned}
 f^{\Psi^x}(a, b, s) &= \frac{1}{s} \iint_{x, y \in \mathbb{R} \times \mathbb{R}} f(x, y) \Psi^x\left(\frac{x-a}{s}, \frac{y-b}{s}\right) dx dy \\
 &= -\frac{\partial}{\partial a} \iint_{x, y \in \mathbb{R} \times \mathbb{R}} f(x, y) \Theta\left(\frac{x-a}{s}, \frac{y-b}{s}\right) dx dy \\
 f^{\Psi^y}(a, b, s) &= \frac{1}{s} \iint_{x, y \in \mathbb{R} \times \mathbb{R}} f(x, y) \Psi^y\left(\frac{x-a}{s}, \frac{y-b}{s}\right) dx dy \\
 &= -\frac{\partial}{\partial b} \iint_{x, y \in \mathbb{R} \times \mathbb{R}} f(x, y) \Theta\left(\frac{x-a}{s}, \frac{y-b}{s}\right) dx dy
 \end{aligned}$$

- The integral $\iint \dots$ is essentially scaled- Θ -smoothed version of f
- $(-f^{\Psi^x}(a, b, s), -f^{\Psi^y}(a, b, s))$ is the *gradient* (a, b) of this function

Recall CANNY's definition

- Let $f \in \mathcal{L}^2(\mathbb{R}^2)$.

The vertex $(x_0, y_0) \in \mathbb{R}^2$ is an *edge vertex* of $f(x, y)$ if

$$|\text{grad}f| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

has a local maximum when passing through (x_0, y_0) in the direction of $(\text{grad}f)(x_0, y_0)$

- This can be tested by computing

$$\left(f^{\Psi^x}(a, b, s)\right)^2 + \left(f^{\Psi^y}(a, b, s)\right)^2$$

over several scale values s

- A vertex which is declared edge vertex over several scales is assumed to be a true edge vertex

Looking at this in the MRA context

- Scaling, wavelet and smoothing (1-dim) are described by

$$\phi(x) = \sqrt{2} \sum_k h_k \phi(2x - k) \quad \psi(x) = \sqrt{2} \sum_k g_k \phi(2x - k)$$

$$\theta(x) = \sqrt{2} \sum_\ell r_\ell \theta(2x - \ell)$$

- Scalierung and wavelet equations for $\Phi^x(x, y) = \phi(x) \theta(y/2)$ and for $\Psi^x(x, y) = \psi(x) \theta(y)$ are

$$\Phi^x(x, y) = 2 \sum_{k, \ell} h_k r_\ell \Phi^x(2x - k, 2y - \ell)$$

$$\Psi^x(x, y) = 2 \sum_{k, \ell} g_k \epsilon_\ell \Phi^x(2x - k, 2y - \ell)$$

where $\epsilon_\ell = \frac{1}{\sqrt{2}} \delta_{\ell,0}$.

Similarly for $\Phi^y(x, y)$ and $\Psi^y(x, y)$

- The HAAR wavelet function $\psi_{haar}(t)$ is the derivative of the smoothing function $\theta(t) = \Delta(t)$:

$$\psi_{haar}(t) = \frac{d}{dt}\Delta(t) \quad \text{where} \quad \Delta(t) = \begin{cases} t & 0 \leq t \leq 1/2 \\ 1 - t & 1/2 \leq t \leq 1 \\ 0 & \text{sonst} \end{cases}$$

- The function $\Delta(t)$ satisfies

$$\Delta(x) + 2\Delta(x - 1/2) + \Delta(x - 1) = 2\Delta(x/2)$$

- which can be written as a scaling equation

$$\Delta(x) = \frac{1}{2} (\Delta(2x) + 2\Delta(2x - 1) + \Delta(2x - 2))$$

- so that

$$\mathbf{r} = \frac{1}{2\sqrt{2}} \langle 1, 2, 1 \rangle$$

- Approximation and detail coefficients are

$$a_{m;k,l}^x = \langle f, \Phi_{2^m,k,l}^x \rangle = \iint f(x,y) \frac{1}{2^m} \Phi^x\left(\frac{x-k}{2^m}, \frac{y-l}{2^m}\right) dx dy$$

$$d_{m;k,l}^x = \langle f, \Psi_{2^m,k,l}^x \rangle = \iint f(x,y) \frac{1}{2^m} \Psi^x\left(\frac{x-k}{2^m}, \frac{y-l}{2^m}\right) dx dy$$

and analogously for $a_{m;k,l}^y$ and $d_{m;k,l}^y$

- Recursions formula for approximation

$$a_{m+1;p,q}^x = \sum_{k,l} h_k r_l a_{m;p+k2^m,q+l2^m}^x$$

- detail coefficients

$$d_{m+1;p,q}^x = \sum_{k,l} g_k \epsilon_l a_{m;p+k2^m,q+l2^m}^x = \frac{1}{\sqrt{2}} \sum_k g_k a_{m;p+k2^m,q}^x$$

- Formulas for $a_{m;k,l}^x$ and $d_{m;k,l}^y$ are analogous

- Scheme for computation (*à trous* algorithm)

$$A_m^x = \left[f^{\Phi^x}(2^m; p, q) \right]_{p,q} \quad A_m^y = \left[f^{\Phi^y}(2^m; p, q) \right]_{p,q}$$

$$D_m^x = \left[f^{\Psi^x}(2^m; p, q) \right]_{p,q} \quad D_m^y = \left[f^{\Psi^y}(2^m; p, q) \right]_{p,q}$$

where $A_0 = A_0^x = A_0^y = [f(p, q)]_{p,q}$

