

The work of Yves Meyer (Abel Prize 2017) Wavelets in harmonic analysis and signal processing

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Olena Shmahalo/Quanta Magazine

Yves Meyer

- Born 19 July 1939
- Studied at the Lycée Carnot in Tunis
- Won French General Student Competition (Concours Général) in Mathematics
- First place, entrance exam, ENS Ulm, 1957
- Professorships
 - Université Strasbourg (1980–1986)
 - Université Paris-Sud (1966–1980)
 - Ecole Polytechnique (1980–1986)
 - Université Paris-Dauphine (1985–1995)
 - ENS-Cachan (1999-2003)
- 2010 Gauss Prize
- 2017 Abel Prize



Source Wikipédia



Brief history of wavelets



Emmanuel Candès















OUTLINE

Construction of wavelet bases

- Meyer wavelet
- The mathematical micoscope
- Multi-resolution analysis
- Applications: coding, etc.

Wavelets and functional analysis

- Wavelets and (fractional) differentiation
- Wavelets and Besov spaces
- Best N-term approximations

Wavelets and sparsity

- Denoising
- Biomedical image reconstruction
- Compressed sensing

Conclusion





The precursors: the continuous wavelet transform

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DECOMPOSITION OF HARDY FUNCTIONS INTO SQUARE INTEGRABLE WAVELETS OF CONSTANT SHAPE*

A. GROSSMANN^{\dagger} and J. MORLET^{\ddagger}

Abstract. An arbitrary square integrable real-valued function (or, equivalently, the associated Hardy function) can be conveniently analyzed into a suitable family of square integrable wavelets of constant shape, (i.e. obtained by shifts and dilations from any one of them.) The resulting integral transform is isometric and self-reciprocal if the wavelets satisfy an "admissibility condition" given here. Explicit expressions are obtained in the case of a particular analyzing family that plays a role analogous to that of coherent states (Gabor wavelets) in the usual L_2 -theory. They are written in terms of a modified Γ -function that is introduced and studied. From the point of view of group theory, this paper is concerned with square integrable coefficients of an irreducible representation of the nonunimodular ax + b-group.

$$W_{\psi}\{f\}(\tau,s) = \int_{\mathbb{R}} f(t) \frac{1}{\sqrt{s}} \psi\left(\frac{t-\tau}{s}\right) \mathrm{d}t = \langle f, \psi_{\mathbf{s},\tau} \rangle$$

$$f(t) = \frac{1}{C_{\psi}} \int_0^\infty \int_{\mathbb{R}} W_{\psi} \{f\}(\tau, s) \psi_{\mathbf{s}, \tau}(t) \mathrm{d}\tau \frac{\mathrm{d}s}{s^2}$$

$$C_{\psi} = \int_{\mathbb{R}} \frac{|\hat{\psi}(\omega)|^2}{\omega} d\omega < \infty$$

natics 009



Jean Morlet (1931-2007)



Alex Grossmann (1930-2019)





Nice, but (strongly) **overcomplete** ...



1. CONSTRUCTION OF WAVELET BASES

Wavelet basis functions

Dilation and translation of a single prototype, but with critical sampling

$$\psi_{i,k} = 2^{-i/2}\psi\left(\frac{x-2^ik}{2^i}\right)$$

- The Meyer wavelet
- Multi-resolution analysis
- Applications to image coding









Littlewood-Paley decomposition / Shannon wavelet



$$\forall f \in L_2(\mathbb{R}) : \quad f(t) = \sum_{j=\infty}^{\infty} \sum_{k \in \mathbb{Z}} \langle f, \psi_{j,k} \rangle \ \psi_{j,k}$$



$$\psi_{j,k}(t) = 2^{-j/2} \psi_{\text{Sha}}\left(\frac{t-2^{j}k}{2^{j}}\right)$$



The Meyer wavelet





$$\forall f \in L_2(\mathbb{R}) : \quad f(t) = \sum_{j=-\infty}^{\infty} \sum_{k \in \mathbb{Z}} \langle f, \psi_{j,k} \rangle \ \psi_{j,k}$$



$$\psi_{j,k}(t) = 2^{-j/2} \psi_{\text{Meyer}} \left(\frac{t - 2^j k}{2^j}\right)$$

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Wavelet transform as a mathematical microscope

Wavelet = Point Spread Function (PSF) of mathematical microscope

- Shape of PSF is the same at all scales
- Magnification by powers of two: 2^i
- Sampling is critical (no redundancy)
- Analysis functions (PSF) are orthogonal
- Resolution can be pushed to ultimate limit \Rightarrow existence of wavelet bases of $L_2(\mathbb{R})$





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Wavelets: on the virtues and applications of the mathematical microscope

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Key words. Deconvolution, denoising, wavelets, image analysis, multiresolution, computational imaging.



Multiresolution analysis: Haar transform revisited



Signal representation

$$s_0(x) = \sum_{k \in \mathbb{Z}} c[k]\varphi(x-k)$$

Scaling function

Multi-scale signal representation

$$s_i(x) = \sum_{k \in \mathbb{Z}} c_i[k] \varphi_{i,k}(x)$$

Multi-scale basis functions

$$\varphi_{i,k}(x) = \varphi\left(\frac{x-2^ik}{2^i}\right)$$

Wavelets: Haar transform revisited

Wavelets: Haar transform revisited

Scaling function

Definition: $\varphi(x)$ is a valid scaling function of $L_2(\mathbb{R})$ iff:

Riesz basis condition

$$\forall c \in \ell_2, \quad A \cdot \|c\|_{\ell_2} \le \left\| \sum_{k \in \mathbb{Z}} c[k] \varphi(x-k) \right\|_{L_2} \le B \cdot \|c\|_{L_2}$$

$$\varphi(x) = \frac{2}{H(1)} \sum_{k \in \mathbb{Z}} h[k] \varphi(2x - k)$$

Partition of unity

$$\sum_{k \in \mathbb{Z}} \varphi(x - k) = 1$$

$$c\|_{\ell_2}$$

$$\hat{\varphi}(\omega) = \prod_{j=1}^{\infty} \frac{H(e^{i\omega/2^j})}{H(1)}$$

Multiresolution analysis of *L*₂

- Multiresolution basis

Two-scale relation $\Rightarrow V_{(i)} \subset V_{(j)}$, for $i \geq j$

Partition of unity

s functions:
$$\varphi_{i,k}(x) = 2^{-i/2} \varphi\left(\frac{x-2^i k}{2^i}\right)$$

• Subspace at resolution *i*: $V_{(i)} = \operatorname{span} \{\varphi_{i,k}\}_{k \in \mathbb{Z}}$

$$\Leftrightarrow \quad \overline{\bigcup_{i \in \mathbb{Z}} V_{(i)}} = L_2(\mathbb{R})$$

From scaling functions to wavelets

• Wavelet bases of L_2 (Mallat-Meyer, 1989)

Theorem

with $g[\cdot] \in \ell_2(\mathbb{Z})$ such that the family of functions

$$\left\{2^{-i/2}\psi\left(\frac{x-2^ik}{2^i}\right)\right\}_{i\in\mathbb{Z},k\in\mathbb{Z}}$$

forms a Riesz (or an orthogonal) basis of $L_2(\mathbb{R})$.

Constructive approach: perfect-reconstruction filterbank

$$\underbrace{\tilde{H}(z^{-1}) \longrightarrow 1}_{\tilde{G}(z^{-1})} \underbrace{\tilde{H}(z^{-1}) \longrightarrow 1}_{\tilde{H}(z^{-1})} \underbrace{\tilde{H}(z^{-1}) \longrightarrow 1}_{\tilde{H}(z^{-1})} \underbrace{\tilde{H}(z^{-1}) \longrightarrow 1}_{\tilde{H}(z^{-1})} \underbrace{\tilde{H}(z^{-1})$$

$$G(z) = \sum_{k \in \mathbb{Z}} g[k] z^{-k}$$

Haar wavelet and 2D basis functions

Tensor-product basis functions

Expansion coefficients

Shortest, orthogonal solutions of the two-scale relation

Two-scale relation:

$$\varphi(x/2) = \sum_{k \in \mathbb{Z}} h[k]\varphi(x-k) \qquad (\mathbf{w}$$

Haar transform (order 1):

$$H_1(z) = 1 + z^{-1}$$

$$\varphi_{\text{Haar}}(x) + \varphi_{\text{Haar}}(x-1)$$

Daubechies of order 2:

$$H_2(z) = \frac{1}{4} \left[\left(1 + \sqrt{3} \right) + \left(3 + \sqrt{3} \right) z^{-1} + \left(3 - \sqrt{3} \right) z^{-2} + \left(1 - \sqrt{3} \right) z^{-3} \right]$$
$$= (1 + z^{-1})^2 P_2(z)$$

Daubechies of order N:

$$H_N(z) = (1 + z^{-1})^N P_N(z)$$

 $\Leftrightarrow \psi$ has N vanishing more

vithout normalization)

ments; i.e.,
$$\int_{\mathbb{R}} x^n \psi(x) dx = 0, n = 0, \dots, N-1$$

Application: Wavelet coding

Wavelet expansion of an image

$$f(\boldsymbol{x}) = \sum_{i,\boldsymbol{k}} \psi_{i,\boldsymbol{k}}(\boldsymbol{x}) w_{i,\boldsymbol{k}}$$

Space-domain representation: f = Ww

66.4 dB

Reconstruction: $\mathbf{f}_N = \mathbf{W}\mathbf{w}_N$

Wavelet-domain representation: $w = W^{-1}f$

0.00%

Discarding "small coefficients"

CDF 9/7 Filters: **Cohen-Daubechies-Feauveau**

Thresholding: $\mathbf{w} \rightarrow \mathbf{w}_N$

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Fractional B-spline wavelets

Remarkable property

Each of these wavelets generates a Riesz basis of $L_2(\mathbb{R})$

$$\psi_{+}^{\alpha}(x/2) = \sum_{k \in \mathbb{Z}} \frac{(-1)^{k}}{2^{\alpha}} \sum_{n \in \mathbb{N}} \binom{\alpha+1}{n} \beta_{*}^{2\alpha+1} (n+k-1) \frac{\Delta_{+}^{\alpha+1}(x-k)_{+}^{\alpha}}{\Gamma(\alpha+1)}$$

Only known wavelet bases that have an explicit time-domain formula !

(Unser & Blu, *SIAM Rev,* 2000)

2. WAVELETS AND FUNCTIONAL ANALYSIS

Wavelets and differentiation

- Wavelets and Besov spaces
- Best N-term approximations

What makes wavelets attractive for mathematicians

- Existence of wavelet bases of $L_2(\mathbb{R}^d)$ (one-to-one representation) Basis functions are dilations and translates of a single template
- Vanishing moments, derivative-like behavior
 ⇒ Sparse representation of piecewise-smooth signals
- Unconditional basis of many function spaces: L_p -Sobolev, Hölder, Besov, ...
- Assessment of local/global regularity from wavelet decay/mixed ℓ_p -norms
- Sparsity and (non-linear) N-term approximation of functions Natural images tend to have few large wavelet coefficients \Rightarrow Wavelet-domain regularization: ℓ_1 -sparsity, compressed sensing, ...

Wavelets and functional spaces

"everything takes place as if the wavelets $\psi(x/a)$ were eigenvectors of the differential operator ∂^s , with corresponding eigenvalue a^{-s} .

Yves Meyer (Wavelets and Operators)

Wavelets and fractional differentiation

Fractional differentiation

Fourier transform: $\hat{f}(\omega) = \mathcal{F}\{f\}(\omega) = \int_{\mathbb{D}} f(x)e^{-i\omega x} dx$

Fractional derivative of order $r: \partial^r f(x) \xrightarrow{\mathcal{F}} (i\omega)^r \hat{f}(\omega)$

Differentiation and scaling $\partial^r \psi(x) = \psi^{(r)}(x) \quad \stackrel{\mathcal{F}}{\longleftrightarrow} \quad (\mathrm{i}\omega)^r \hat{\psi}(\omega)$ $\partial^r \psi(x/a) = a^{-r} \psi^{(r)}(x/a) \quad \stackrel{\mathcal{F}}{\longleftrightarrow} \quad (\mathrm{i}\omega)^r |a| \hat{\psi}(a\omega)$

Property: the "derivative" wavelet $\psi^{(r)}$ also generates a biorthogonal basis of $L_2(\mathbb{R})$ provided that $\psi \in W_2^r$ and r < N (number of vanishing moments of ψ).

$$) = a^{-r} |a| (ia\omega)^r \hat{\psi}(a\omega)$$

$$a^{-r}$$

$$\underbrace{w_j[k]}_{[k]} \psi_{j,k}^{(r)}(x)$$

Wavelets and Sobolev spaces

Sobolev space of order
$$s$$
 f has s derivatives in L_2 -sense $f \in W_2^s(\mathbb{R}) \iff f, \ \partial^s f \in L_2(\mathbb{R})$
$$W_2^s(\mathbb{R}) = \left\{ f = \mathcal{F}^{-1}\{\hat{f}\} : \int_{\omega \in \mathbb{R}} (1 + |\omega|^{2s}) |\hat{f}(\omega)|^2 \frac{\mathrm{d}\omega}{2\pi} \triangleq \|f\|_{W_2^s}^2 < +\infty \right\}$$

Equivalent norm in wavelet domain

$$\|w\|_{\ell_{2},s} \triangleq \left(\|c_{j_{0}}\|_{\ell_{2}}^{2} + \sum_{j=-\infty}^{j_{0}} \|2^{-js}w_{j}\|_{\ell_{2}}^{2} \right)^{\frac{1}{2}} \\ \sim \|\partial^{s}f\|_{L_{2}}^{2}$$

 $||f||_{W_2^s} \sim ||w||_{\ell_2,s} \quad \Leftrightarrow \quad C_1 ||w||_{\ell_2,s} \le ||f||_{W_2^s} \le C_2 ||w||_{\ell_2,s}$

Orthogonal wavelet expansion

$$c_{j_0}[k] = \langle f, \varphi_{j_0,k} \rangle$$

$$w_j[k] = \langle f, \psi_{j,k} \rangle$$

Wavelets and Besov spaces

Besov space of order s > 0

 $f \in B_q^s(L_p(\mathbb{R})) \Leftrightarrow \begin{cases} (i) \ f \in L_p(\mathbb{R}) \\ (ii) \text{ there exists a sequence of "smooth" for a such that } \|f - g_j\|_{L_p} \leq 2^{-js} \epsilon_j \text{ and } with \end{cases}$

Besov space and multiresolution analysis (Meyer 1990)

Explicit approximation sequence: $f_j = \sum_{k \in \mathbb{Z}} \langle f, \varphi_{j,k} \rangle \varphi_{j,k}$,

$$f \in B_q^s(L_p(\mathbb{R})) \Leftrightarrow \begin{cases} f \in L_p(\mathbb{R}) \\ \|f - f_j\|_{L_p} \le 2^{js} \epsilon_j, \ \epsilon \in \ell_q \end{cases} \Leftrightarrow \begin{cases} f_{j_0} \in L_p(\mathbb{R}) \\ \|\partial^s r_j\|_{L_p} \le \epsilon_j, \ \epsilon \in \ell_q \end{cases}$$

s derivatives in L_p -sense q: fine-tuning parameter that controls decay across scales

Equivalent norm in wavelet domain

$$\|f\|_{B^{s}_{q}(L_{p}(\mathbb{R}))} \sim \left[\left(2^{-j_{0}(\frac{1}{2} - \frac{1}{p})} \|c_{j_{0}}\|_{\ell_{p}} \right)^{q} + \sum_{j=-\infty}^{j_{0}} \left(2^{-j(\frac{1}{2} - \frac{1}{p})} \|2^{-js}w_{j}\|_{\ell_{p}} \right)^{q} \right]^{\frac{1}{q}}$$

 $\sim \|\partial^s r_i\|_{L_p}$

" functions
$$g_j \in L_p(\mathbb{R}), j \in \mathbb{N}$$

d $\|\partial^{m_0}g_j\|_{L_p} \leq 2^{(m_0-s)j}\epsilon_j$
h $\epsilon \in \ell_q$ and $m_0 \geq s$

$$r_j = \sum_{k \in \mathbb{Z}} \langle f, \psi_{j,k} \rangle \, \psi_{j,k}$$

Wavelets and non-linear approximation

Equivalent Besov norm in wavelet domain

$$\|f\|_{B^{s}_{q}(L_{p}(\mathbb{R}^{d}))} \sim \left[\sum_{j=-\infty}^{+\infty} \left(2^{-j(s+\frac{d}{2}-\frac{d}{p})} \|w_{j}\|_{\ell_{p}}\right)^{q}\right]^{\frac{1}{q}} =$$

Critical regularity exponent: $s = \frac{d}{p} - \frac{d}{2}$ For $p = q \in [1, 2]$: $\ell_p(\mathbb{Z}^d) \subseteq \ell_2(\mathbb{Z}^d) \Rightarrow B_p^s(L_p(\mathbb{R}^d)) \subseteq L_2(\mathbb{R}^d)$

N-term wavelet expansions: $\Sigma_N = \left\{ g = \sum_{j,k \in \Lambda_N} c_{j,k} \psi_{j,k}, c_{j,k} \in \mathbb{R}, \operatorname{card}(\Lambda_N) \leq N \right\}$

Best *N*-term wavelet approximation: $f_N = \arg \max_{g \in S} f_{g}$

$$\|f - f_N\|_{L_2(\mathbb{R}^d)} \le \frac{C}{N^r} \|f\|_{B_p^s(L_p(\mathbb{R}^d))}$$
 with $r =$

(d = dimension of domain)

 $= \|w\|_{\ell_1}$ If p = q = 1 and $s = \frac{d}{2}$

$$\min_{i \in \Sigma_N} \|f - g\|_{L_2} = \sum_{j,k \in \Lambda_N(f)} w_j[k]\psi_{j,k}$$

 $= \frac{s}{d}$

(DeVore, Cohen 1998)

3. WAVELETS AND SPARSITY

- Wavelet-based denoising
- Image reconstruction by iterative shrinkage thresholding
- Compressed sensing

 $\min \|\mathbf{x}\|_{\ell_1}$ subject to $\|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2^2 \le \sigma^2$ \mathbf{X}

[Figuereido et al. 2003, Daubechies et al. 2004]

[Donoho 1995]

[Donoho et al., 2005 Candès-Tao, 2006, ...]

Denoising and wavelet-domain/Besov regularization

Measurement model

Wavelet domain Space domain $\mathbf{y} = \mathbf{f} + \mathbf{n} \quad \Leftrightarrow \quad w_i[\mathbf{k}] = \tilde{w}_i[\mathbf{k}] + n_i[\mathbf{k}] \quad \text{(additive white noise)}$

Regularized least-squares signal estimation

- Regularization functional: $R(\tilde{f}) = \|\tilde{\mathbf{w}}\|_{\ell_1} = \sum \sum |\tilde{w}_j[\mathbf{k}]| \sim \|\tilde{f}\|_{B_1^1(L_1(\mathbb{R}^2))}$
- Variational formulation of denoising problem:

$$\tilde{\mathbf{f}} = \arg\min_{\mathbf{f}} \left(\|\mathbf{y} - \mathbf{f}\|_2^2 + \lambda \|\mathbf{W}^T \mathbf{f}\|_1 \right)$$

Equivalent wavelet-domain solution (by Parseval)

$$\tilde{\mathbf{f}} = \mathbf{W}\tilde{\mathbf{w}}$$
 with $\tilde{\mathbf{w}} = \arg\min_{\mathbf{v}} \left(\|\underbrace{\mathbf{W}^T\mathbf{y}}_{\mathbf{w}} - \mathbf{v}\|_2^2 + \lambda \right)$

Orthogonal wavelet transform: $\mathbf{W}^T \mathbf{W} = \mathbf{I}$

Standard Color Image

Input PSNR=18.59 dB

Denoised with OWT SURE-LET

Output PSNR = 31.91 dB

(Luisier et al., IEEE Trans. Image Proc. 2007)

SURE-LET Optimized thresholds

Denoised with UWT SURE-LET

SURE-LET Optimized thresholds + redundant wavelet transform

Output PSNR = 33.27 dB

(Luisier et al., IEEE Trans. Image Proc. 2007)

2D + time SURE-LET denoising (DWT) : C-elegance embryo

Wavelet-regularized image reconstruction

 $\mathbf{g} = \mathbf{H}\mathbf{f} + \mathbf{n}$

Hypotheses:

- System matrix H is known (physics)
- $\mathbf{f} = \mathbf{W}\mathbf{w}$ has a "sparse" wavelet expansion

Reconstruction as a (convex) optimization problem $\tilde{\mathbf{f}} = \arg\min_{\mathbf{f}} \left(\|\mathbf{g} - \mathbf{H}\mathbf{f}\|_{2}^{2} + \lambda \|\widetilde{\mathbf{W}}^{-1}\right)$ data consistency regularization $\tilde{\mathbf{f}} = \mathbf{W}\tilde{\mathbf{w}}$ with $\tilde{\mathbf{w}} = \arg\min$

Theory of compressed sensing (Donoho et al., 2005, Candès-Tao, 2006] Conditions on A for perfect signal recovery from few measurements when $\|\mathbf{w}\|_0 < K_0$

$$\mathbf{\hat{f}} \parallel_{\ell_1}$$

 $\sim \|\widetilde{f}\|_{B^1_1(L_1(\mathbb{R}^2))}$

$$\left(\|\mathbf{g} - \mathbf{A}\mathbf{w}\|_2^2 + \lambda \|\mathbf{w}\|_{\ell_1} \right)$$

Equivalent system matrix: A = HW

3D deconvolution of widefield stack

Maximum intensity projections of $384 \times 448 \times 260$ image stacks; Leica DM 5500 widefield epifluorescence microscope with a $63 \times$ oil-immersion objective; C. Elegans embryo labeled with Hoechst, Alexa488, Alexa568; wavelet regularization (Haar), 3 decomposition levels for X-Y, 2 decomposition levels for Z.

(Vonesch-U., IEEE TIP 2009)

Application: Parallel MRI reconstruction

 $S(\mathbf{r})f(\mathbf{r})$

Parallel MRI: several receiving coils, known sensitivities Challenging reconstruction: few k-space samples

k-space domain

$$g(\mathbf{k}) = \int S(\mathbf{r}) f(\mathbf{r}) \mathrm{e}^{\mathrm{j}\langle \mathbf{r}, \mathbf{k} \rangle} \mathrm{d}\mathbf{r}$$

Wavelet-regularized reconstruction of MRI

 L_2 regularization (Laplacian)

Standard approach (CG)

(Guerquin-Kern et al. IEEE Trans. Med. Im. 2012)

 ℓ_1 wavelet regularization

WFISTA algorithm

REVISTA MATEMÁTICA IBEROAMERICANA Vol. 2, N.^{os} 1 y 2, 1986

Ondelettes et bases hilbertiennes

P.G. Lemarié et Y. Meyer En hommage à A.P. Calderón

Cette base convient à tous les espaces fonctionnels classiques: espaces de Sobolev, de Besov, de Hardy... qui se traduisent isomorphiquement en des espaces de suites.

10 P.G. LEMARIÉ ET Y. MEYER

L'espace BMO(\mathbb{R}^n) n'est pas séparable et ne possède donc pas de base inconditionnelle. Nous le remplaçons par la version séparable VMO(\mathbb{R}^n) qui est la fermeture, pour la norme de BMO(\mathbb{R}^n), de l'espace $S(\mathbb{R}^n)$ des fonctions de test.

Théorème 3. La suite $\psi_{O}^{(\epsilon)}$, $\epsilon \in E$, $Q \in \mathbb{Q}$, est une base inconditionnelle pour $L^{p}(\mathbb{R}^{n}; dx), 1$

Théorème 5. Une distribution tempérée f (modulo les polynômes) appartient à $B_q^{s,p}$ si et seulement si $\sup_{\epsilon \in E} |\langle f, \psi_Q^{(\epsilon)} \rangle| = \alpha(k,j)$ vérifie

(6.1)
$$\left(\sum_{j=-\infty}^{\infty} \left\{ \left(\sum_{k\in\mathbb{Z}^n} (\alpha(k,j))^p \right)^{1/p} 2^{j(s+n(1/2-1/p))} \right\}^q \right)^{1/q} < +\infty$$

(avec les changements usuels si $p = +\infty$ ou $q = +\infty$).

P.G. Lemarié et Y. Meyer Centre de Mathématiques de l'Ecole Polytechnique Plateau de Palaiseau-91128 Paraiseau Cedex «Unité Associée au C.N.R.S. n.º 169»

Ce travail a été effectué dans le cadre de la «R.C.P. ondelettes» du C.N.R.S. M727.1285, Décembre 1985.

Conclusion: Impact of wavelets

Yves Meyer

Functional analysis

Numerical analysis

Stochastic processes

Fractals and multi-fractals

Albert Cohen

Stéphane Jaffard

