

WAVELET ANALYSIS OF FRACTIONAL BROWNIAN MOTION IN MULTIFRACTAL TIME

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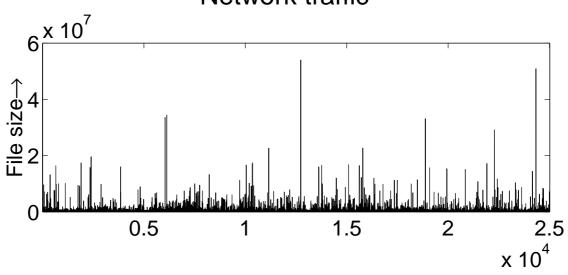
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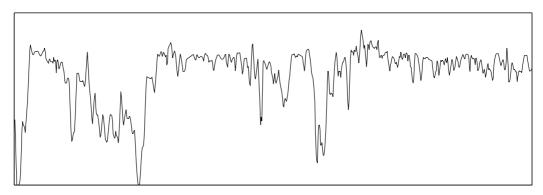
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Multifractals in Nature

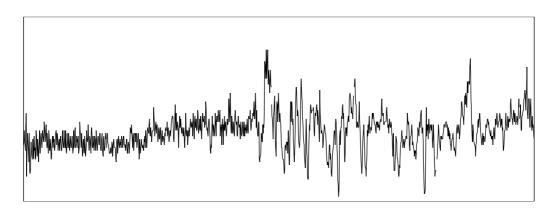




Well-log data



Heart bit inter-arrival time



Wavelet characterization of Hölder Exponent

Wavelet Decomposition

Definition

$$c_{j,k} = 2^{-j} \int \psi^*(2^{-j}t - k) x(t) dt, (j,k) \in \mathbb{Z}^2$$

Vanishing moments

$$\int t^r \psi(t) dt = 0, r = 0, ..., \mathcal{R} - 1.$$

Oscillatory behavior measure

x has local Hölder regularity $\alpha(t)$ at time t

$$\Downarrow$$

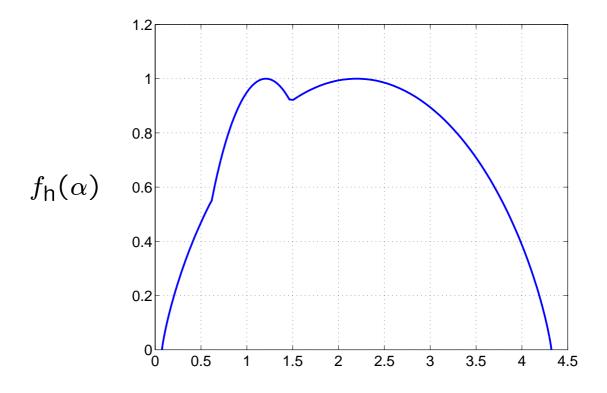
$$\alpha(t)$$
: $|c_{j,k}| = O\left(2^{j\alpha(t)}\right), k2^j \to t$

Hölder Spectra (Regularity Spectra)

Typically, a process will possess many different singularity strengths. The frequency (in t) of occurrence of a given singularity strength α is measured by the *multifractal spectrum*

Hausdorff spectrum (geometric spectrum)

$$f_{\mathsf{h}}(\alpha) = \dim_{\mathcal{H}} \{t : \alpha(t) = \alpha\}$$



Hölder Spectra

Grain Spectrum (Large Deviation principle)

An adaptation of the Box-counting dimension to the multifractal case

• Define a iso- α 2^j-covering

$$M^{j}(\alpha, \varepsilon) := \# \left\{ k : |\alpha_{k}^{j} - \alpha| < \varepsilon \right\}$$

with "free" choice of Grain exponent

$$\alpha_k^j := \frac{1}{j} \log \sup_{s,t} \{|x(t) - x(s)| : (k-1)2^j \le s \le t \le (k+2)2^j \}$$

$$:= \frac{1}{j} \log |c_{j,k}|$$

$$(M^j(\alpha, \varepsilon)) = \# \{k : 2^{j(\alpha+\varepsilon)} \le |c_{j,k}| \le 2^{j(\alpha-\varepsilon)} \})$$

$$:= ???$$

The Grain Spectrum reads

$$f_g(\alpha) := \lim_{\varepsilon \to 0} \lim_{j \to -\infty} -\frac{1}{j} \log_2 M^j(\alpha, \varepsilon)$$

$$f_h(\alpha) \leq f_g(\alpha)$$

Hölder Spectra

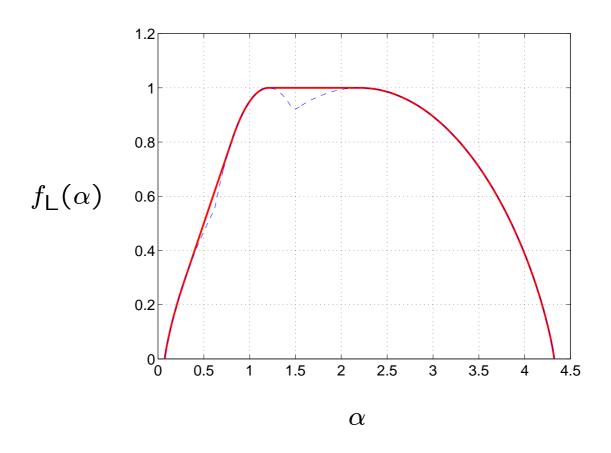
Legendre spectrum (statistical spectrum)

Log moment generating function

$$\sum_{k} |c_{j,k}|^{q} = O\left(2^{jT(q)}\right)$$

wavelet-based Legendre Spectrum

$$f_{\mathsf{L}}(\alpha) := \inf_{q} (\alpha \, q - T(q)) = T^*(\alpha)$$



$$f_h(\alpha) \leq f_g(\alpha) \leq f_L(\alpha)$$

Multiplicative Random Cascades

The most well known processes with truly multifractal properties

Scaling --> Strong dependence

Multiplicative --> Log-Normal

Tree → Fast algorithms (wavelets)

Binomial cascade: a paradigm

i.i.d. random variables

$$\left\{ \mu_k^i, \; \middle| \; i = 0, -1, -2, \dots \atop k = 0, \dots, 2^{-i} - 1 \right\}$$

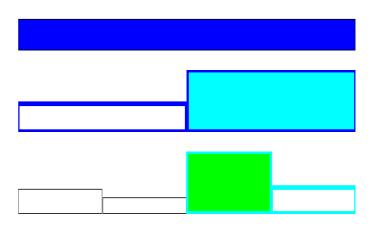
Define the random measure μ on dyadic intervals

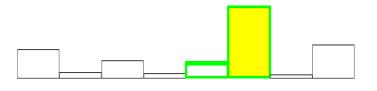
$$\mu([k_j 2^j, (k_j + 1)2^j])$$

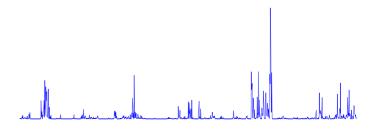
$$= \mu_{k_0}^0 \cdot \mu_{k_1}^1 \cdots \mu_{k_j}^j$$

with mass conservation

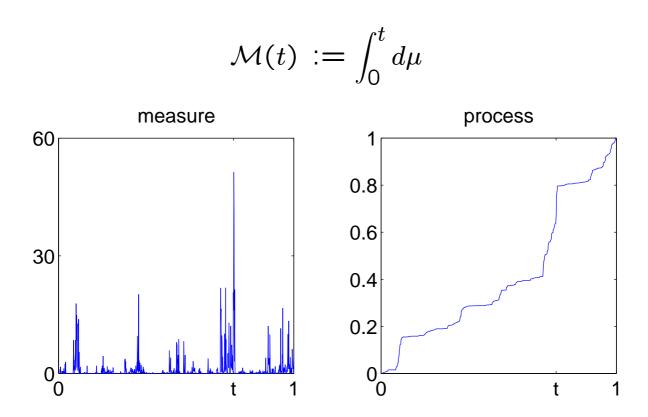
$$\mu_{2k}^{i+1} + \mu_{2k+1}^{i+1} = 1$$







Multifractal Cascade Process



Rescaling property (self similarity)

$$\mathcal{M}(2^{j}(k+t)) - \mathcal{M}(2^{j}(k+s)) \stackrel{d}{=} W_{j} \cdot (\mathcal{M}(t) - \mathcal{M}(s))$$
with $W_{j} \stackrel{d}{=} \mu_{k_{0}}^{0} \cdot \mu_{k_{1}}^{1} \cdots \mu_{k_{j}}^{j}$

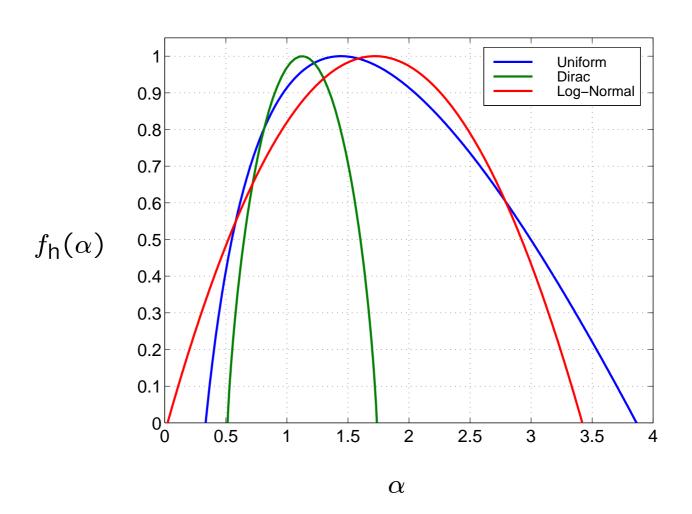
Stationarity of increments / Scaling of moments

$$\mathbb{E}|\mathcal{M}(t) - \mathcal{M}(s)|^q = |t - s|^{T(q)}$$

(binomial process: holds for $t = k2^j$, $s = (k+1)2^j$ and for stationary multifractals in general e.g. Lévy motions, T(q) = qH)

True multifractal spectrum - Closed form
 Depends on the distribution law of the multipliers

$$\mu_k^j \ \stackrel{d}{=} \left\{ \begin{array}{ll} M_0 & \text{if k is even} \\ M_1 & \text{if k is odd} \end{array} \right.$$



Monotonous increasing process

Fractional Brownian Motion

Unique process that:

- 1. is Gaussian
- 2. is statistically self-similar

$$B_H(\lambda t) \stackrel{d}{=} \lambda^H B_H(t), \ 0 < H < 1$$

3. has stationary increments

$$G_H(t) = B_H(t + \Delta) - B_H(t)$$

Self-similarity implies non stationarity

$$\mathbb{E}B_H(t)B_H(s) = \frac{\sigma^2}{2} \left(|t|^{2H} + |s|^{2H} - |t - s|^{2H} \right)$$

ullet Long-range dependence when H>1/2

$$\mathbb{E}[G_H(t)G_H(t+\tau)] \approx \tau^{2H-2}, \, \tau \gg \Delta$$

- Mono-fractal process: $\alpha(t) = H, \forall t$
 - → degenerated (trivial) singularity spectrum

Multifractional Processes

Previous attempts exist towards "Multifractal Processes"

1992 Generalized Weierstrass functions (*P. Flandrin, P. Gonçalv*ès)

1998 Construction of continuous functions with prescribed local regularity

(Y. Meyer, K. Daoudi, J. Lévy Véhel)

1998 Generalized Multifractional Brownian Motion (A. Ayache, J. Lévy Véhel)

1999 Locally self-similar processes (S. Cohen, J. Istas, A. Benassi)

others...

Multifractional Motion

Let:

- 1. $B_H(t)$ be a fractional Brownian Motion
- 2. $\mathcal{M}(t)$ be a multiplicative process

and consider the compound process:

$$\mathcal{B}(t) := B_H(\mathcal{M}(t))$$

Fractional Brownian Motion in Multifractal Time

Covariance structure

$$\mathbb{E}\mathcal{B}(t)\mathcal{B}(s) = \frac{\sigma^2}{2}\mathbb{E}\left[|\mathcal{M}(t)|^{2H} + |\mathcal{M}(s)|^{2H} - |\mathcal{M}(t) - \mathcal{M}(s)|^{2H}\right]$$

Special cases

-
$$H=1/2$$

$$\mathcal{G}(k):=\mathcal{B}((k+1)\Delta)-\mathcal{B}(k\Delta)$$
 is decorrelated, but dependent

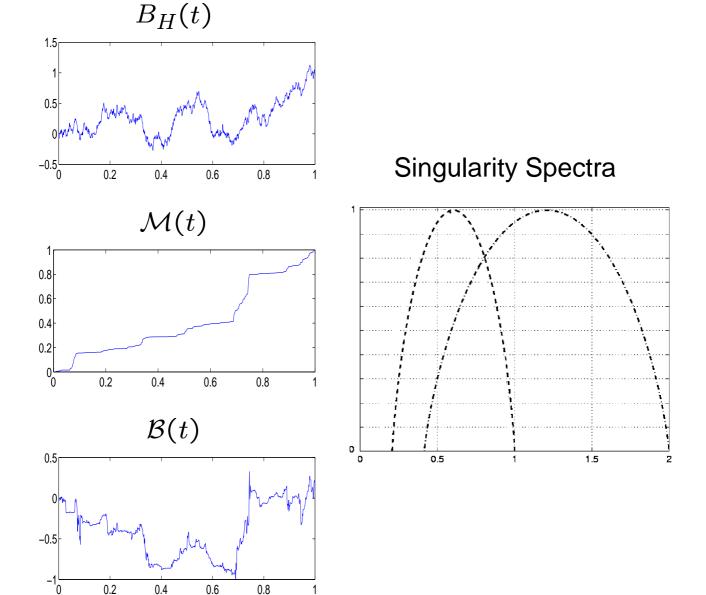
$$-H > 1/2$$

B exhibits long range dependence

Multifractional Motion

 $\mathcal{B}(t)$ inherits from the rich multifractal structure of the underlying multiplicative cascade process $\mathcal{M}(t)$

$$f_h^{\mathcal{B}}(\alpha) = f_h^{\mathcal{M}}\left(\frac{\alpha}{H}\right)$$



Wavelet Analysis of Multifractional Motions

A wavelet-based multifractal spectrum estimator relies on the empirical high order moments of the wavelet coefficients

$$T(q) := \lim_{j o -\infty} rac{1}{j} \log \sum_k |c_{j,k}|^q$$

Potential obstacles:

- non-stationarity of multifractional process B can carry over to the wavelet coefficient series of its decomposition
- Long Range Dependence intrinsic to \mathcal{B} , (H > 1/2) may affect the convergence of the empirical estimator

Statistics of Wavelet Decomposition

Identical distributions

$$c_{j,k} \stackrel{d}{=} (W_j)^H c_{0,0}, \text{ (with } W_j \stackrel{d}{=} \mu_{k_0}^0 \cdot \mu_{k_1}^1 \cdots \mu_{k_j}^j)$$

 ψ : admissible wavelet with compact support \mathcal{M} : verifies rescaling property B_H : self-similar process

Wide sense stationarity

$$\mathbb{E}c_{j,k}c_{j,k'} = -\frac{\sigma^2}{2}2^{-j}\int \psi(t)\int |s|^{T(2H)}\psi(t+2^{-j}s-(k-k'))ds dt$$

 \mathcal{M} : satisfies to scaling of moments for q=2H $\mathbb{E}|\mathcal{M}(t)-\mathcal{M}(s)|^{2H}=|t-s|^{T(2H)}$ Covariance structure of \mathcal{B}

The wavelet decomposition of a fBm in multifractal time is stationary at each scale

Statistics of Wavelet Decomposition

Fast decay of the correlation

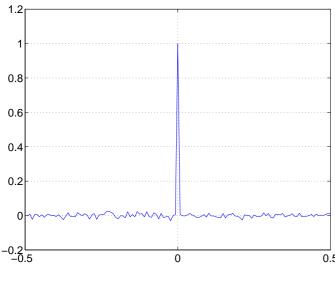
$$\mathbb{E}c_{j,k}c_{j,k'} \approx O\left(|k-k'|^{T(2H)-2\mathcal{R}}\right), |k-k'| \to \infty$$

 ψ : \mathcal{R} vanishing moments $\lim_{\nu \to 0} |\Psi(\nu)|^2 = |\nu|^{2\mathcal{R}}$

inc. of
$$\mathcal{B}$$
: $T(2H)-2>-1 \rightarrow \mathsf{LRD}$

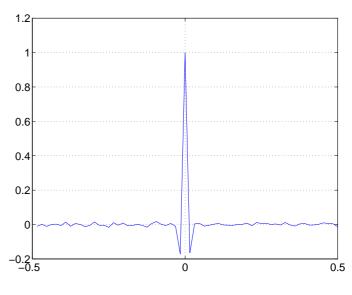
$$c_{j,k}$$
: $T(2H) - 2\mathcal{R} < -1 \rightarrow \text{no LRD}$

$$R = 1 \text{ (Haar)} - H = 0.5$$



time lag
$$\tau$$

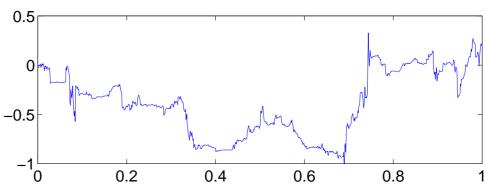
$$R = 2 - H = 0.8$$



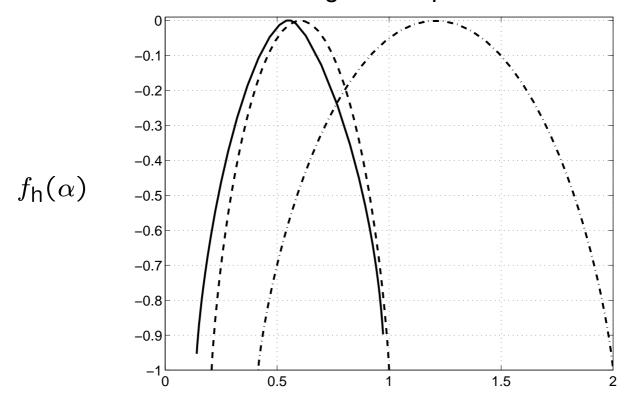
time lag au

Legendre Spectrum Estimation

Multifractional Motion $\mathcal{B}(t)$



Wavelet based Legendre Spectrum estimate



Conclusion

- multifractals: varying degree of local variability (volatility in economics, variability in biomedical,...)
- wavelets: powerful estimation tool with favorable statistical properties
 - fBm in multifractal time: versatile process with multifractal structure and LRD

Wavelet characterization of Hölder Exponent

x(t): a real time process

 $0 < \alpha(t) < 1$: local regularity exponent (Hölder)

$$\forall s |x(s) - x(t)| < c |s - t|^{\alpha(t)}$$

Wavelet Decomposition

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Vanishing moments

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Oscillatory behavior measure

x has local Hölder regularity $\alpha(t)$ at time t

$$\Downarrow$$

$$\alpha(t) = \sup_{\alpha} \left\{ \alpha : |c_{j,k}| = O\left(2^{j\alpha}\right), k2^{j} \to t \right\}$$