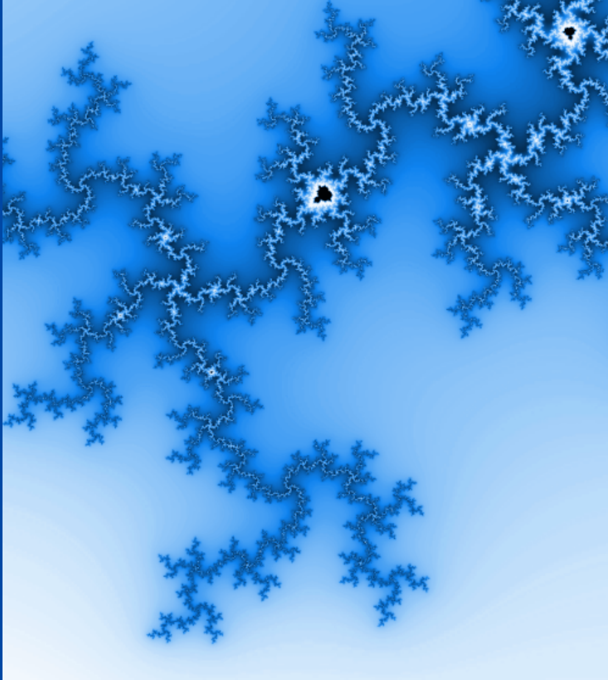
Numerical simulation of Hermite processes

31st Annual Meeting of the Royal Statistical Society of Belgium – Ghent

Laurent Loosveldt

8th November 2024

LIÈGE université
Mathématique



Main definitions

A stochastic process $\{X_t\}_{t \geq 0}$ has:

- stationary increments if, for every $h > 0$, the stochastic processes

$$\{X_t\}_{t \geq 0} \text{ and } \{X_{t+h} - X_h\}_{t \geq 0}$$

  are equal in finite-dimensional distributions.

Main definitions

A stochastic process $\{X_t\}_{t\geq 0}$ has:

- stationary increments if, for every $h > 0$, the stochastic processes

  $$\{X_t\}_{t\geq 0} \text{ and } \{X_{t+h} - X_h\}_{t\geq 0}$$

  are equal in finite-dimensional distributions.
- is H-self-similar if, for every $c > 0$, the stochastic processes

  $$\{X_{ct}\}_{t\geq 0} \text{ and } \{c^H X_t\}_{t\geq 0}$$

  are equal in finite-dimensional distributions.

Long-range dependence

If $\{X_t\}_{t\geq 0}$ is centred with stationary increments, we consider the correlation kernel

$$\rho(k-\ell) := \mathbb{E}[(X_{k+1}-X_k)(X_{j+1}-X_j)] \quad j,k \in \mathbb{N}.$$

Long-range dependence

If $\{X_t\}_{t\geq 0}$ is centred with stationary increments, we consider the correlation kernel

$$\rho(k-\ell) := \mathbb{E}[(X_{k+1}-X_k)(X_{j+1}-X_j)] \quad j,k \in \mathbb{N}.$$

The process $\{X_t\}_{t\geq 0}$ has long-range dependence if

$$\sum_{j\in\mathbb{Z}} |\rho(j)| = \infty.$$

Correlation decays slowly as the lag tends to infinity.

Applications

Such phenomena arise, for instance, in

- astronomy,
- biology,
- climatology,
- hydrology,
- image processing,
- internet traffic modelling,
- mathematical finance,
- physics.

Applications

Such phenomena arise, for instance, in

- astronomy,
- biology,
- climatology,
- hydrology,
- image processing,
- internet traffic modelling,
- mathematical finance,
- physics.

We need good models !

Gaussian case : Fractional Brownian Motion

Definition

Given $H \in (0,1)$, a fractional Brownian motion of Hurst parameter H is a centred continuous Gaussian process $\{B_t^H\}_{t \geq 0}$ with covariance function

$$\mathbb{E}[B_t^H B_s^H] = \frac{1}{2}(t^{2H} + s^{2H} - |t-s|^{2H}).$$

Gaussian case : Fractional Brownian Motion

Definition

Given $H \in (0,1)$, a fractional Brownian motion of Hurst parameter H is a centred continuous Gaussian process $\{B_t^H\}_{t\geq 0}$ with covariance function

$$\mathbb{E}[B_t^H B_s^H] = \frac{1}{2}(t^{2H} + s^{2H} - |t-s|^{2H}).$$

$$\left\{ \frac{1}{c_H} \left(\int_{-\infty}^{0} ((t-u)^{H-\frac{1}{2}} - (-u)^{H-\frac{1}{2}})\, dB(u) + \int_0^t (t-u)^{H-\frac{1}{2}}\, dB(u) \right) \right\}_{t\geq 0}$$

Gaussian case : Fractional Brownian Motion

Definition

Given $H \in (0,1)$, a fractional Brownian motion of Hurst parameter H is a centred continuous Gaussian process $\{B_t^H\}_{t\geq 0}$ with covariance function

$$\mathbb{E}[B_t^H B_s^H] = \frac{1}{2}(t^{2H} + s^{2H} - |t-s|^{2H}).$$

$$\left\{ \frac{1}{c_H} \left(\int_{-\infty}^{0} ((t-u)^{H-\frac{1}{2}} - (-u)^{H-\frac{1}{2}})\, dB(u) + \int_0^t (t-u)^{H-\frac{1}{2}}\, dB(u) \right) \right\}_{t\geq 0}$$

It has stationary increments and is H-self-similar.

Gaussian case : Fractional Brownian Motion

Definition

Given $H \in (0,1)$, a fractional Brownian motion of Hurst parameter H is a centred continuous Gaussian process $\{B_t^H\}_{t\geq 0}$ with covariance function

$$\mathbb{E}[B_t^H B_s^H] = \frac{1}{2}(t^{2H} + s^{2H} - |t-s|^{2H}).$$

$$\left\{ \frac{1}{c_H} \left(\int_{-\infty}^{0} ((t-u)^{H-\frac{1}{2}} - (-u)^{H-\frac{1}{2}})\, dB(u) + \int_0^t (t-u)^{H-\frac{1}{2}}\, dB(u) \right) \right\}_{t\geq 0}$$

It has stationary increments and is H-self-similar. If $H > \frac{1}{2}$, it has long-range dependence.

Non-Gaussian case

Definition

Given $d \in \mathbb{N}$ and $H \in (1/2, 1)$, the Hermite process of order d and Hurst parameter H is defined as

$$\frac{1}{c_H}\left\{\int_{\mathbb{R}^d}\left(\int_0^t \prod_{\ell=1}^{d}(s-x_\ell)_+^{\frac{H-1}{d}-\frac{1}{2}}\,ds\right)dB(x_1)\ldots dB(x_d)\right\}_{t\geq 0}$$

Non-Gaussian case

Definition

Given $d \in \mathbb{N}$ and $H \in (1/2, 1)$, the Hermite process of order d and Hurst parameter H is defined as

$$\frac{1}{c_H}\left\{\int_{\mathbb{R}^d}\left(\int_0^t \prod_{\ell=1}^{d}(s-x_\ell)_+^{\frac{H-1}{d}-\frac{1}{2}}\,ds\right)dB(x_1)\dots dB(x_d)\right\}_{t\geq 0}$$

- $d = 1$, it is the Fractional Brownian Motion;

Non-Gaussian case

Definition

Given $d \in \mathbb{N}$ and $H \in (1/2, 1)$, the Hermite process of order d and Hurst parameter H is defined as

$$\frac{1}{c_H}\left\{\int_{\mathbb{R}^d}\left(\int_0^t \prod_{\ell=1}^{d}(s-x_\ell)_+^{\frac{H-1}{d}-\frac{1}{2}}\,ds\right)dB(x_1)\ldots dB(x_d)\right\}_{t\geq 0}$$

- $d = 1$, it is the Fractional Brownian Motion;
- $d \geq 2$, it is a non-Gaussian process;

Non-Gaussian case

Definition

Given $d \in \mathbb{N}$ and $H \in (1/2, 1)$, the Hermite process of order d and Hurst parameter H is defined as

$$\frac{1}{c_H}\left\{\int_{\mathbb{R}^d}\left(\int_0^t \prod_{\ell=1}^{d}(s-x_\ell)_+^{\frac{H-1}{d}-\frac{1}{2}}\,ds\right) dB(x_1)\dots dB(x_d)\right\}_{t\geq 0}$$

- $d = 1$, it is the Fractional Brownian Motion;
- $d \geq 2$, it is a non-Gaussian process;
- has stationary increments, is H-self-similar with long-range dependence.

Simulations ?

$d = 1$ (Fractional Brownian Motion)

Abry, Meyer, Sellan and Taqqu, in successive works from 1995 to 1999, present a Wavelet-based synthesis for Fractional Brownian motion

Simulations ?

$d = 1$ (Fractional Brownian Motion)

Abry, Meyer, Sellan and Taqqu, in successive works from 1995 to 1999, present a Wavelet-based synthesis for Fractional Brownian motion

$d = 2$ (Rosenblatt process)

Pipiras, in 2004, give a wavelet-type expansion of the Rosenblatt process.

Simulations ?

$d = 1$ (Fractional Brownian Motion)

Abry, Meyer, Sellan and Taqqu, in successive works from 1995 to 1999, present a Wavelet-based synthesis for Fractional Brownian motion

$d = 2$ (Rosenblatt process)

Pipiras, in 2004, give a wavelet-type expansion of the Rosenblatt process.
This expansion is exploited in 2006, together with Abry, to obtain a wavelet-based synthesis of the Rosenblatt process

Simulations ?

$d = 1$ (Fractional Brownian Motion)

Abry, Meyer, Sellan and Taqqu, in successive works from 1995 to 1999, present a Wavelet-based synthesis for Fractional Brownian motion

$d = 2$ (Rosenblatt process)

Pipiras, in 2004, give a wavelet-type expansion of the Rosenblatt process.
This expansion is exploited in 2006, together with Abry, to obtain a wavelet-based synthesis of the Rosenblatt process

$d \geq 3$

Pipiras, in his paper from 2004, raised the question of providing a wavelet-type expansion for any Hermite processes.

Wavelet approximation for deterministic functions

Two smooth functions:

- the scaling function ϕ
- the mother wavelet ψ

Wavelet approximation for deterministic functions

Two smooth functions:

- the scaling function ϕ
- the mother wavelet ψ

Fix a “resolution” J

Wavelet approximation for deterministic functions

Two smooth functions:

- the scaling function ϕ
- the mother wavelet ψ

Fix a "resolution" J

$$f \in L^2(\mathbb{R}^d)$$

$\swarrow$ $\searrow$

Projection onto the subspace spanned by

$$\left\{\otimes_{\ell=1}^{d} 2^{J/2}\phi(2^J \cdot - k_\ell)\right\}_{\mathbf{k}\in\mathbb{Z}^d}$$

$$\sum_{\mathbf{k}} \langle f, \otimes_{\ell=1}^{d} 2^{J/2}\phi(2^J \cdot - k_\ell)\rangle \otimes_{\ell=1}^{d} 2^{J/2}\phi(2^J \cdot - k_\ell)$$

APPROXIMATION

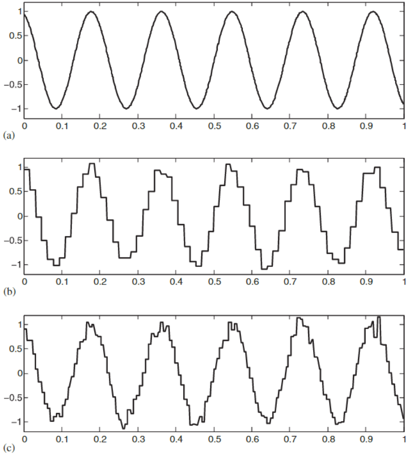
Projection onto the subspace spanned by

$$\left\{\otimes_{\ell=1}^{d} 2^{j_\ell/2}\psi(2^{j_\ell} \cdot - k_\ell) : \mathbf{k}\in\mathbb{Z}^d, \max_{1\le\ell\le d} j_\ell \ge J\right\}$$

$$\sum_{\mathbf{j},\mathbf{k}} \langle f, \otimes_{\ell=1}^{d} 2^{j_\ell/2}\psi(2^{j_\ell} \cdot - k_\ell)\rangle \otimes_{\ell=1}^{d} 2^{j_\ell/2}\psi(2^{j_\ell} \cdot - k_\ell)$$

DETAILS

Multiresolution analysis



Wavelet approximation for stochastic integral

$$I_d : L^2(\mathbb{R}^d) \to L^2(\Omega) : f \mapsto \int_{\mathbb{R}^d} f \, dB(x_1) \ldots dB(x_d)$$

is a quasi-isometry.

Wavelet approximation for stochastic integral

$$I_d : L^2(\mathbb{R}^d) \to L^2(\Omega) : f \mapsto \int_{\mathbb{R}^d} f\, dB(x_1)\dots dB(x_d)$$

is a quasi-isometry.

$$f \in L^2(\mathbb{R}^d)$$

$$\swarrow \qquad \searrow$$

$\sum_{\mathbf{k}} \langle f, \otimes_{\ell=1}^d 2^{J/2}\phi(2^J \cdot - k_\ell)\rangle \otimes_{\ell=1}^d 2^{J/2}\phi(2^J \cdot - k_\ell)$
APPROXIMATION

$\sum_{\mathbf{j},\mathbf{k}} \langle f, \otimes_{\ell=1}^d 2^{j_\ell/2}\psi(2^{j_\ell} \cdot - k_\ell)\rangle \otimes_{\ell=1}^d 2^{j_\ell/2}\psi(2^{j_\ell} \cdot - k_\ell)$
DETAILS

Wavelet approximation for stochastic integral

$$I_d : L^2(\mathbb{R}^d) \to L^2(\Omega) : f \mapsto \int_{\mathbb{R}^d} f \, dB(x_1) \dots dB(x_d)$$

is a quasi-isometry.

$$I_d(f) \in L^2(\Omega)$$

$$\swarrow \qquad \searrow$$

$\sum_{\mathbf{k}} \langle f, \otimes_{\ell=1}^d 2^{J/2}\phi(2^J \cdot - k_\ell)\rangle I_d\left(\otimes_{\ell=1}^d 2^{J/2}\phi(2^J \cdot - k_\ell)\right)$

APPROXIMATION

$\sum_{\mathbf{j},\mathbf{k}} \langle f, \otimes_{\ell=1}^d 2^{j_\ell/2}\psi(2^{j_\ell} \cdot - k_\ell)\rangle I_d\left(\otimes_{\ell=1}^d 2^{j_\ell/2}\psi(2^{j_\ell} \cdot - k_\ell)\right)$

DETAILS

Wavelet approximation for chaotic processes

We consider stochastic processes of the form

$$\{I_d(K(t,\bullet))\}_{t\geq 0}$$

with, for all $t \geq 0$, $K(t,\bullet) \in L^2(\mathbb{R}^d)$. For the Hermite process, we have $K(t,\mathbf{x}) = \frac{1}{c_H} \int_0^t \prod_{\ell=1}^d (s - x_\ell)_+^{\frac{H-1}{d} - \frac{1}{2}} \, ds$.

Wavelet approximation for chaotic processes

We consider stochastic processes of the form

$$\{I_d(K(t,\bullet))\}_{t\geq 0}$$

with, for all $t \geq 0$, $K(t,\bullet) \in L^2(\mathbb{R}^d)$. For the Hermite process, we have $K(t,\mathbf{x}) = \frac{1}{c_H} \int_0^t \prod_{\ell=1}^d (s-x_\ell)_+^{\frac{H-1}{d}-\frac{1}{2}}\, ds.$

Fix $t \geq 0$,

$$X_t$$

$$\swarrow \qquad \searrow$$

$$\underbrace{\sum_{\mathbf{k}} \langle K(t,\bullet), \otimes_{\ell=1}^d 2^{J/2}\phi(2^J \cdot - k_\ell)\rangle I_d\left(\otimes_{\ell=1}^d 2^{J/2}\phi(2^J \cdot - k_\ell)\right)}_{\text{APPROXIMATION}} \qquad \underbrace{\sum_{\mathbf{j},\mathbf{k}} \langle K(t,\bullet), \otimes_{\ell=1}^d 2^{j_\ell/2}\psi(2^{j_\ell} \cdot - k_\ell)\rangle I_d\left(\otimes_{\ell=1}^d 2^{j_\ell/2}\psi(2^{j_\ell} \cdot - k_\ell)\right)}_{\text{DETAILS}}$$

Wavelet approximation for chaotic processes

We consider stochastic processes of the form

$$\{I_d(K(t,\bullet))\}_{t\geq 0}$$

with, for all $t \geq 0$, $K(t,\bullet) \in L^2(\mathbb{R}^d)$. For the Hermite process, we have $K(t,\mathbf{x}) = \frac{1}{c_H}\int_0^t \prod_{\ell=1}^d (s-x_\ell)_+^{\frac{H-1}{d}-\frac{1}{2}}\, ds.$

Fix $t \geq 0$,

$$X_t$$

$\swarrow$ $\searrow$

$\sum_{\mathbf{k}} \langle K(t,\bullet), \otimes_{\ell=1}^d 2^{J/2}\phi(2^J\cdot - k_\ell)\rangle I_d\left(\otimes_{\ell=1}^d 2^{J/2}\phi(2^J\cdot - k_\ell)\right)$
APPROXIMATION

$\sum_{\mathbf{j},\mathbf{k}} \langle K(t,\bullet), \otimes_{\ell=1}^d 2^{j_\ell/2}\psi(2^{j_\ell}\cdot - k_\ell)\rangle I_d\left(\otimes_{\ell=1}^d 2^{j_\ell/2}\psi(2^{j_\ell}\cdot - k_\ell)\right)$
DETAILS

But, generally, we want a stronger convergence: almost surely uniformly on compact sets.

(A. Ayache, J. Hamonier, L. L. - 2024)

The random series

$$X_{H,J}^{(d)}(t) = 2^{-J(H-1)} \sum_{\mathbf{k}\in\mathbb{Z}^d} \sigma_{J,\mathbf{k}}^{(H)} \int_0^t \prod_{\ell=1}^{d} \Phi_{\Delta}^{(1/2+\frac{H-1}{d})}(2^J s - k_\ell)\, ds, \qquad (1)$$

is almost surely, for each $J \in \mathbb{N}$, uniformly convergent in t on each compact interval $I \subset \mathbb{R}_+$. Moreover, for all such I, there exists an almost surely finite random variable (depending on I) for which one has, almost surely, for each $J \in \mathbb{N}$,

$$\|X_H^{(d)} - X_{H,J}^{(d)}\|_{I,\infty} = \left\| \sum_{\substack{(\mathbf{j},\mathbf{k})\in(\mathbb{Z}^d)^2 \\ \max_{\ell\in[[1,d]]} j_\ell \geq J}} 2^{(\frac{H-1}{d})(j_1+\cdots+j_d)} \varepsilon_{\mathbf{j},\mathbf{k}} \int_0^t \prod_{\ell=1}^{d} \psi_{h_\ell}(2^{j_\ell} s - k_\ell)\, ds \right\|_{I,\infty} \leq C J^{\frac{d}{2}} 2^{-J(H-1/2)}.$$

$\sigma_{J,\mathbf{k}}^{(H)}$

$$\sigma_{J,\mathbf{k}}^{(\mathbf{h})} = \sum_{m=0}^{\lfloor d/2 \rfloor} (-1)^m \sum_{P \in \mathscr{P}_m^{(d)}} \prod_{r=1}^{m} \mathbb{E}[Z_{J,k_{\ell_r}}^{(1/2+\frac{H-1}{d})} Z_{J,k_{\ell'_r}}^{(1/2+\frac{H-1}{d})}] \prod_{s=m+1}^{d-m} Z_{J,k_{\ell''_s}}^{(1/2+\frac{H-1}{d})}. \qquad (2)$$

where, for $J \in \mathbb{Z}$, we consider the sequence $(g_{J,k}^{\phi})_{k\in\mathbb{Z}}$ of i.i.d. $\mathcal{N}(0,1)$ Gaussian random variable defined, for all $k \in \mathbb{Z}$, by $g_{J,k}^{\phi} := 2^{J/2} \int_{\mathbb{R}} \phi(2^J x - k)\, dB(x)$. and for $\delta \in (-1/2, 1/2)$, the Gaussian FARIMA $(0,\delta,0)$ sequence $(Z_{J,\ell}^{(\delta)})_{\ell\in\mathbb{Z}}$ associated to $(g_{J,k}^{\phi})_{k\in\mathbb{Z}}$ is given, for all $\ell \in \mathbb{Z}$, by

$$Z_{J,\ell}^{(\delta)} := g_{J,\ell}^{\phi} + \sum_{p=1}^{+\infty} \gamma_p^{(\delta)} g_{J,\ell-p}^{\phi}, \text{ with } \delta_p^{(\delta)} := \frac{\delta\,\Gamma(p+\delta)}{\Gamma(p+1)\Gamma(\delta+1)}$$

“Approximation process”

$$X_{H,J}^{(d)}(t) = 2^{-J(H-1)} \sum_{\mathbf{k}\in\mathbb{Z}^d} \sigma_{J,\mathbf{k}}^{(H)} \int_0^t \prod_{\ell=1}^{d} \Phi_{\Delta}^{(1/2+\frac{H-1}{d})}(2^J s - k_\ell)\, ds,$$

with $\widehat{\Phi}_{\Delta}^{(\delta)}(\xi) = \left(\frac{1-e^{-i\xi}}{i\xi}\right)^{\delta} \widehat{\phi}(\xi)$

Not computable, only because of the series.

Strategy

To deduce the inequality

$$\|X_H^{(d)} - X_{H,J}^{(d)}\|_{I,\infty} = \left\| \sum_{\substack{(\mathbf{j},\mathbf{k})\in(\mathbb{Z}^d)^2 \\ \max\limits_{\ell\in[[1,d]]} j_\ell \geq J}} 2^{(\frac{H-1}{d})(j_1+\cdots+j_d)} \varepsilon_{\mathbf{j},\mathbf{k}} \int_0^t \prod_{\ell=1}^d \psi_{h_\ell}(2^{j_\ell}s - k_\ell)\,ds \right\|_{I,\infty} \leq C J^{\frac{d}{2}} 2^{-J(H-1/2)}.$$

we somehow remarked that this rate of convergence is mainly determined by the terms in the series for which the corresponding indices belongs to

$$D_j^1(t) := \{k \in \mathbb{Z} : [k2^{-j} - 2^{-ja}, k2^{-j} + 2^{-ja}] \subseteq [0,t]\} \text{ with } a \in (1/2, 1)$$

Strategy

To deduce the inequality

$$\|X_H^{(d)} - X_{H,J}^{(d)}\|_{I,\infty} = \left\| \sum_{\substack{(\mathbf{j},\mathbf{k})\in(\mathbb{Z}^d)^2 \\ \max_{\ell\in[[1,d]]} j_\ell \geq J}} 2^{(\frac{H-1}{d})(j_1+\cdots+j_d)} \varepsilon_{\mathbf{j},\mathbf{k}} \int_0^t \prod_{\ell=1}^d \psi_{h_\ell}(2^{j_\ell}s - k_\ell)\, ds \right\|_{I,\infty} \leq C J^{\frac{d}{2}} 2^{-J(H-1/2)}.$$

we somehow remarked that this rate of convergence is mainly determined by the terms in the series for which the corresponding indices belongs to

$$D_j^1(t) := \{k \in \mathbb{Z} : [k2^{-j} - 2^{-ja}, k2^{-j} + 2^{-ja}] \subseteq [0,t]\} \text{ with } a \in (1/2,1)$$

Set

$$\mathcal{J}_J^1(t) := \{\mathbf{k} \in (D_J^1(t))^d : \max_{\ell,\ell'\in[[1,d]]} |k_\ell - k_{\ell'}| \leq 2^{\varepsilon J}\} \text{ with } \varepsilon > 0.$$

Simulation process

(A. Ayache, J. Hamonier, L. L. - 2024)

For all $J \in \mathbb{N}$, the *simulation process at scale* J of the generalized Hermite process $\{X_H^{(d)}(t)\}_{t\in\mathbb{R}_+}$ is the process defined, for all $t \in \mathbb{R}_+$, by

$$S_{H,J}^{(d)}(t) = 2^{-JH} \sum_{\mathbf{k}\in \mathscr{J}_J^1(t)} \sigma_{J,\mathbf{k}}^{(\mathbf{h})} \int_{\mathbb{R}} \prod_{\ell=1}^{d} \Phi_{\Delta}^{(1/2+\frac{H-1}{d})}(s-k_\ell)\, ds. \tag{3}$$

For any compact interval $I \subset \mathbb{R}_+$, there exists an almost surely finite random variable C (depending on I) for which one has, almost surely, for each $J \in \mathbb{N}$,

$$\|X_H^{(d)} - S_{H,J}^{(d)}\|_{I,\infty} \leq C J^{\frac{d}{2}} 2^{-J(H-1/2)}. \tag{4}$$

Python routine (using some R packages) for the Hermite processes of order 1,2 and 3 available upon request.

Python routine (using some R packages) for the Hermite processes of order 1,2 and 3 available upon request.

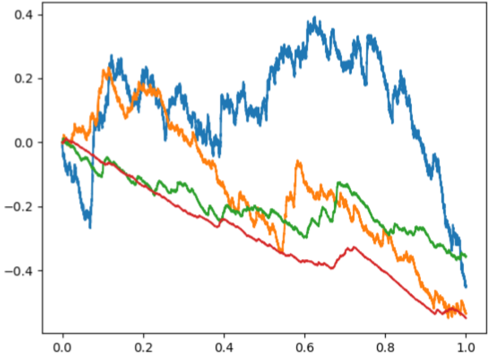


Figure: Paths of the Rosenblatt process of Hurst parameter $0{,}6$ (blue), $0{,}7$ (orange), $0{,}8$ (green) and $0{,}9$ (red).

Python routine (using some R packages) for the Hermite processes of order 1,2 and 3 available upon request.

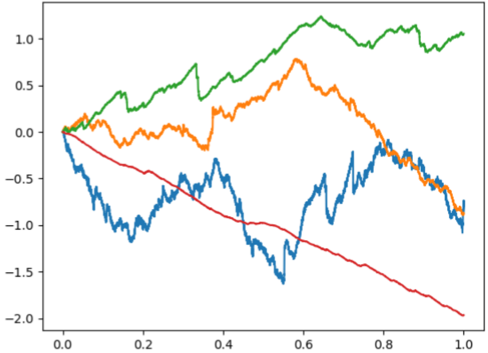


Figure: Paths of the Hermite process of order 3 of Hurst parameter $0,6$ (blue), $0,7$ (orange), $0,8$ (green) and $0,9$ (red).

Python routine (using some R packages) for the Hermite processes of order 1,2 and 3 available upon request.

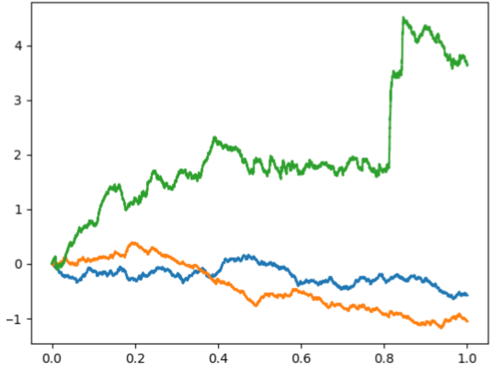


Figure: Paths of the Fractional Brownian Motion (blue), the Rosenblatt process (orange) and the Hermite process of order 3 (green) with Hurst parameter $0,6$.

Python routine (using some R packages) for the Hermite processes of order 1,2 and 3 available upon request.

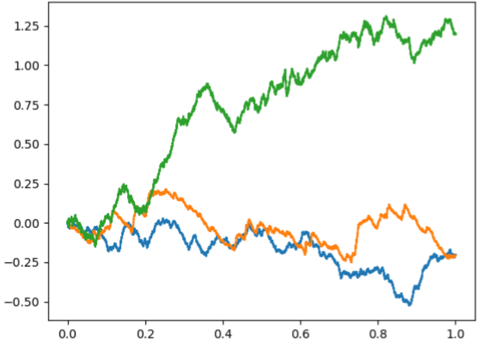


Figure: Paths of the Fractional Brownian Motion (blue), the Rosenblatt process (orange) and the Hermite process of order 3 (green) with Hurst parameter $0,7$.

Python routine (using some R packages) for the Hermite processes of order 1,2 and 3 available upon request.

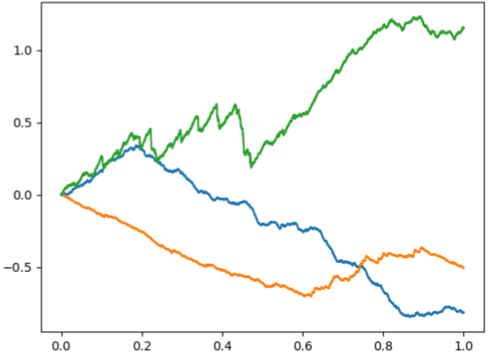


Figure: Paths of the Fractional Brownian Motion (blue), the Rosenblatt process (orange) and the Hermite process of order 3 (green) with Hurst parameter $0,8$.

Python routine (using some R packages) for the Hermite processes of order 1,2 and 3 available upon request.

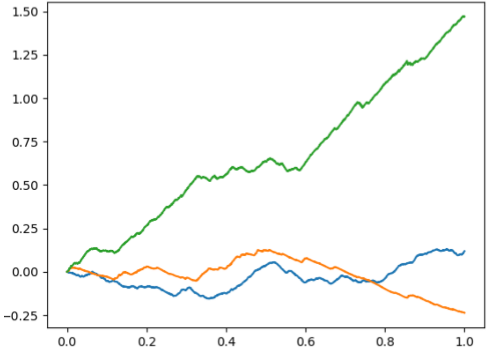


Figure: Paths of the Fractional Brownian Motion (blue), the Rosenblatt process (orange) and the Hermite process of order 3 (green) with Hurst parameter $0{,}9$.

Applications (work in progress)

- test the numerical efficiency of statistical estimator for the Hurst parameters of the Hermite processes

Applications (work in progress)

- test the numerical efficiency of statistical estimator for the Hurst parameters of the Hermite processes
- statistical inference for the order of the process.

Applications (work in progress)

- test the numerical efficiency of statistical estimator for the Hurst parameters of the Hermite processes
- statistical inference for the order of the process.

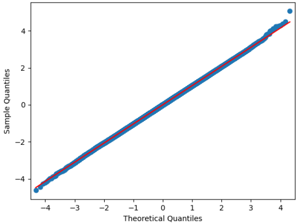


Figure: QQplot for the distribution of a fractional Brownian motion, compared with a $\mathcal{N}(0,1)$

Applications (work in progress)

- test the numerical efficiency of statistical estimator for the Hurst parameters of the Hermite processes
- statistical inference for the order of the process.

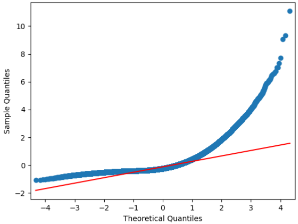


Figure: QQplot for the distribution of a Rosenblatt process, compared with a $\mathcal{N}(0,1)$

Applications (work in progress)

- test the numerical efficiency of statistical estimator for the Hurst parameters of the Hermite processes
- statistical inference for the order of the process.

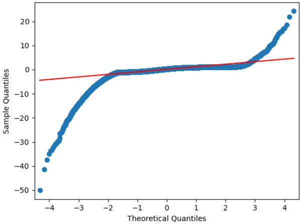


Figure: QQplot for the distribution of a Hermite process of order 3, compared with a $\mathcal{N}(0,1)$