

Rough Differential Equations Reflected in a Time-Dependent Convex Set: Theoretical, Numerical and Statistical Results

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Introduction

The model

Consider the stochastic differential equation

$$X(t) = X_0 + \int_0^t b(X(s))ds + \int_0^t \sigma(X(s))dB(s) \quad (1)$$

where B is a fractional Brownian motion.

How to constrain X to stay in a closed convex set?

If B is a Brownian motion, in Itô's calculus framework:

- Invariance condition on (b, σ) .
- Skorokhod reflection problem.

Objective

If B is a fractional Brownian motion, to extend the second method in the rough paths framework.

References

Existence (only) with a constant constraint set:

- Aida (2015,2016)

Existence and uniqueness with a constant constraint set:

- Besalu & al. (2012): nonnegative constraints.
- Deya & al. (2016): 1-dimensional constraint set.
- Richard & al. (2019): penalisation in dimension 1.

Existence and uniqueness with a time-dependent constraint set:

- Falkowski & Slominski (2015): $H \in]1/2, 1[$ and a time-dependent cuboid constraint.
- Castaing, M & Raynaud de Fitte (2018): Existence for $H \in]1/3, 1[$. Uniqueness and approximation for σ constant.

Statistical inference:

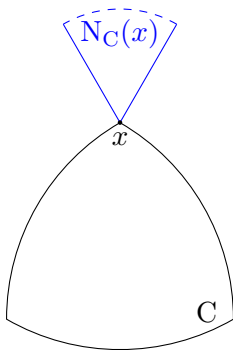
- M (2019): Nonparametric estimation of the trend.

The Skorokhod Reflection Problem

Preliminaries: normal cone

For every $x \in \mathbb{R}^e$,

$$N_C(x) := \{s : \forall y \in C, \langle s, y - x \rangle \leq 0\}.$$



Preliminaries: the differential measure and its variation

Consider $f \in C^{1\text{-var}}([0, T], \mathbb{R}^e)$.

The vector measure Df , defined on $\mathcal{B}([0, T])$ by

$$Df([s, t]) := f(t) - f(s),$$

is the differential measure of f .

Its variation $|Df|$ is the measure defined on $\mathcal{B}([0, T])$ by

$$|Df|(A) := \sup \left\{ \sum_{i=1}^n \|Df(B_i)\| ; n \in \mathbb{N}^*, \right.$$

$B_1, \dots, B_n \in \mathcal{B}([0, T])$ pairwise disjoint s.t. $B_i \subset A$ $\}$.

Preliminaries: the differential measure and its variation

In the sequel,

$$\dot{f} := \frac{dDf}{d|Df|}.$$

Example. If the map f is absolutely continuous, then

$$f(t) = \int_0^t \dot{f}(s) ds.$$

The Moreau sweeping process

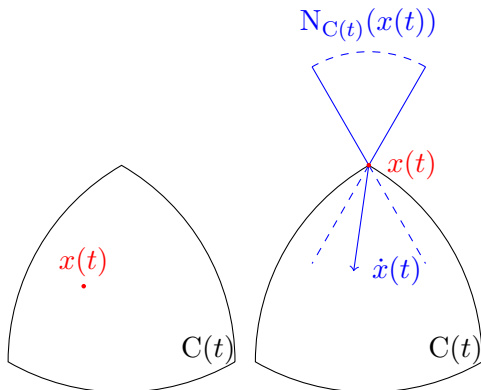
is defined by the differential inclusion

$$\begin{cases} -\dot{x}(t) \in N_{C(t)}(x(t)) & |Dx|\text{-a.e.} \\ x(0) = x_0 \in C(0) \end{cases} \quad (2)$$

where $C : [0, T] \rightrightarrows \mathbb{R}^e$ is a convex compact valued multifunction continuous for the Hausdorff distance.

The Moreau sweeping process: some pictures

Two situations:



The Monteiro-Marques theorem

If there exist $a \in \mathbb{R}^e$ and $r > 0$ such that

$$\bar{B}_e(a, r) \subset C(t) ; \forall t \in [0, T],$$

then (2) has a unique continuous solution of finite 1-variation x such that

$$\|x\|_{1\text{-var}, T} \leq \frac{1}{2r} \|x_0 - a\|^2 \quad (3)$$

The rough perturbed sweeping process

is defined by

$$X(t) = \underbrace{\int_0^t b(X(u))du + \int_0^t \sigma(X(u))dB(u)}_{H(t)} + Y(t) \quad (4)$$

where

$$\begin{cases} -\dot{Y}(t) \in N_{C(t)-H(t)}(Y(t)) \text{ } |DY|\text{-a.e.} \\ Y(0) = X_0 \end{cases} \quad (5)$$

Existence and uniqueness of the solution

A continuity theorem (Castaing et al. (2014))

Consider a continuous function $h : [0, T] \rightarrow \mathbb{R}^e$ and

$$\begin{cases} v_h(t) = h(t) + w_h(t) \\ -\dot{w}_h(t) \in N_{C(t)-h(t)}(w_h(t)) \text{ } |Dw_h|\text{-a.e.} \\ w_h(0) = x_0 \in C(0) \end{cases} \quad (6)$$

For every sequence of continuous functions $(h_n)_{n \in \mathbb{N}}$, if

$$h_n \rightarrow h \text{ uniformly,}$$

then

$$(v_{h_n}, w_{h_n}) \rightarrow (v_h, w_h) \text{ uniformly.}$$

Existence of solutions to (4)-(5)

If there exists a continuous function $\gamma : [0, T] \rightarrow \mathbb{R}^e$ such that

$$\overline{B}_e(\gamma(t), r) \subset C(t) ; \forall t \in [0, T],$$

then (4)-(5) has at least one solution belonging to

$$\bigcap_{p>1/H} C^{p\text{-var}}([0, T], \mathbb{R}^e).$$

Existence of solutions to (4)-(5): sketch of proof

Consider the Picard scheme

$$\left\{ \begin{array}{l} X_n(t) = H_n(t) + Y_n(t) \\ H_n(t) = \int_0^t b(X_{n-1}(u)) du + \int_0^t \sigma(X_{n-1}(u)) dB(u) \\ -\dot{Y}_n(t) \in N_{C(t)-H_n(t)}(Y_n(t)) \quad |DY_n| \text{-a.e. with } Y_n(0) = X_0 \end{array} \right. .$$

A compactness argument using (3) and the previous continuity theorem give that $(X_n, Y_n)_{n \in \mathbb{N}}$ has a converging subsequence.

Its limit is a solution to (4)-(5).

Uniqueness of the solution to (4)-(5) with σ constant

Assume that σ is constant. Then, (4)-(5) is equivalent to

$$\begin{cases} X(t) = H(t) + Y(t) \\ H(t) = \int_0^t b(X(s))ds + \sigma B(t) \\ -\dot{Y}(t) \in N_{C(t)-H(t)}(Y(t)) \text{ |DY|-a.e. with } Y(0) = X_0 \end{cases} \quad (7)$$

If there exists a continuous function $\gamma : [0, T] \rightarrow \mathbb{R}^e$ such that

$$\overline{B}_e(\gamma(t), r) \subset C(t) ; \forall t \in [0, T],$$

then (4)-(5) has a unique solution belonging to

$$\bigcap_{p > 1/H} C^{p\text{-var}}([0, T], \mathbb{R}^e).$$

Uniqueness of the solution to (7): sketch of proof

Consider two solutions (X, Y) and (X^*, Y^*) to (7).

Steps:

1. There exists a control function ω such that:

$$\begin{aligned} \|X(t) - X^*(t)\|^2 &\leq \omega(0, t) \|X - X^*\|_{\infty, t}^2 \\ &\quad + c \int_0^t \langle X(u) - X^*(u), d(Y - Y^*)(u) \rangle. \end{aligned}$$

2. By the monotonicity of $N_{C(u)}(\cdot)$; $u \in [0, T]$,

$$\int_0^t \langle X(u) - X^*(u), d(Y - Y^*)(u) \rangle \leq 0.$$

3. By dissecting $[0, T]$ in small subintervals, $(X, Y) = (X^*, Y^*)$.

Uniqueness of the solution to (4)-(5): NSC

Consider two solutions (X, Y) and (X^*, Y^*) to (4)-(5).

The monotonicity of the normal cone is not sufficient to prove that

$$\|X - X^*\|_{p\text{-var}, t} = 0.$$

It is true if and only if

$$\int_s^t \langle R_X(s, u) - R_{X^*}(s, u), d(Y - Y^*)(u) \rangle \leq 0 \quad (8)$$

Numerical scheme

Approximation of the solution to (7)

For $n \in \mathbb{N}^*$, consider the approximation scheme

$$\begin{cases} X_0^n = x_0 \\ X_{k+1}^n = p_{\mathbb{C}(t_{k+1}^n)}^\perp (X_k^n + \mathbf{H}^n(t_{k+1}^n) - \mathbf{H}^n(t_k^n)) \end{cases} \quad (9)$$

where

$$\mathbf{H}^n(t) - \mathbf{H}^n(t_k^n) = b(X_k^n)(t - t_k^n) + \sigma(\mathbf{B}(t) - \mathbf{B}(t_k^n)) ; t \in [t_k^n, t_{k+1}^n[\quad (10)$$

Convergence of the scheme (9)-(10)

By putting

$$X^n(t) := X_k^n ; t \in [t_k^n, t_{k+1}^n[,$$

if C is Hölder continuous for the Hausdorff distance and there exists a continuous function $\gamma : [0, T] \rightarrow \mathbb{R}^e$ such that

$$\overline{B}_e(\gamma(t), r) \subset C(t) ; \forall t \in [0, T],$$

then $(X^n)_{n \in \mathbb{N}^*}$ converges uniformly pathwise to X .

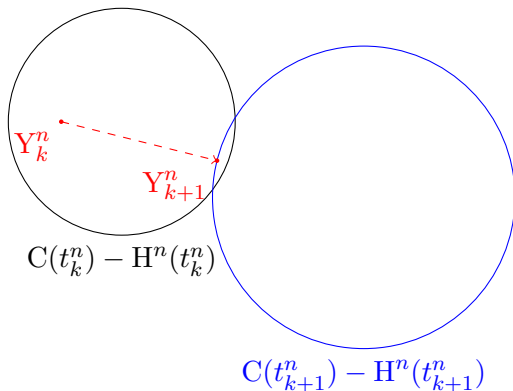
Convergence of the scheme (9)-(10): sketch of proof

Consider

$$Y_{k+1}^n := X_{k+1}^n - H^n(t_{k+1}^n) = p_{C(t_{k+1}^n) - H^n(t_{k+1}^n)}^\perp(Y_k^n)$$

and put

$$Y^n(t) := Y_k^n ; t \in [t_k^n, t_{k+1}^n[.$$



Convergence of the scheme (9)-(10): sketch of proof

Steps:

1. By a compactness argument, any subsequence of $(H^n)_{n \in \mathbb{N}^*}$ has a subsequence converging in $C^0([0, T], \mathbb{R}^e)$. Its limit is denoted by H^* .
2. $(Y^n)_{n \in \mathbb{N}^*}$ is a Cauchy sequence in $C_{\text{piecewise}}^0([0, T], \mathbb{R}^e)$.
3. The limit Y^* of $(Y^n)_{n \in \mathbb{N}^*}$ satisfies

$$\langle z - H^*(\tau), Y^*(t) - Y^*(s) \rangle \geq \frac{1}{2} (\|Y^*(t)\|^2 - \|Y^*(s)\|^2) \quad (11)$$

for every $(s, t) \in \Delta_T$, $\tau \in [s, t]$ and $z \in \bigcap_{\tau \in [s, t]} C(\tau)$.

4. So, (X^*, Y^*) with $X^* := H^* + Y^*$ coincides with (X, Y) .

Statistical inference

A nonparametric estimator of the trend: preliminaries

The solution to (7) is denoted by X_σ , $e = 1$ and $H > 1/2$.

Let us provide a converging estimator of the trend

$$\tau := x - X(0)$$

of Problem (7), where

$$\begin{cases} x(t) = h(t) + y(t) \\ h(t) = \int_0^t b(x(s)) ds \\ -\dot{y}(t) \in N_{C(t)-h(t)}(y(t)) \quad |Dy| \text{-a.e. with } y(0) = X(0) \end{cases} \quad (12)$$

A nonparametric estimator of the trend

Consider

$$\hat{\tau}_\sigma(t) := \frac{1}{h_\sigma} \int_0^t \int_0^T \mathcal{K}\left(\frac{s-u}{h_\sigma}\right) dX_\sigma(s) du,$$

where \mathcal{K} is a smooth kernel such that $\mathcal{K}^{-1}(\{0\})^c =]A, B[$.

Convergence of the estimator

If C is Lipschitz continuous for the Hausdorff distance, then

$$\sup_{t \in [0, T]} \mathbb{E}(|\hat{\tau}_\sigma(t) - \tau(t)|^2) \leq c(\sigma^2 + h_\sigma^2 + \sigma^2 h_\sigma^{2H-2}) \quad (13)$$

The best possible rate is reached for $h_\sigma = \sigma^{1/(2-H)}$. Then,

$$\lim_{\sigma \rightarrow 0} \sigma^{\alpha-2/(2-H)} \sup_{t \in [0, T]} \mathbb{E}(|\hat{\tau}_\sigma(t) - \tau(t)|^2) = 0 ; \forall \alpha > 0.$$

Convergence of the estimator: sketch of proof

On the one hand, by Slominski and Wojciechowski (2013),

$$\|Y_\sigma - y\|_{\infty, T} \leq \|H_\sigma - h\|_{\infty, T}.$$

Then, by Gronwall's lemma:

$$\mathbb{E}(\|X_\sigma - x\|_{\infty, T}^2) + \mathbb{E}(\|Y_\sigma - y\|_{\infty, T}^2) \leq \mathbf{c}\sigma^2 \quad (14)$$

Convergence of the estimator: sketch of proof

On the other hand,

$$\widehat{\tau}_\sigma(t) - \tau(t) = \alpha_\sigma(t) + \beta_\sigma(t) + \gamma_\sigma(t) + \zeta_\sigma(t) + \eta_\sigma(t),$$

where

$$\alpha_\sigma(t) := \int_0^t \int_0^T \mathcal{K}_{h_\sigma}(s-u)(b(\mathbf{X}_\sigma(s)) - b(x(s)))dsdu,$$

$$\beta_\sigma(t) := \int_0^t \int_0^T \mathcal{K}_{h_\sigma}(s-u)b(x(s))dsdu - \int_0^t b(x(u))du,$$

$$\gamma_\sigma(t) := \sigma \int_0^t \int_0^T \mathcal{K}_{h_\sigma}(s-u)dB(s)du,$$

$$\zeta_\sigma(t) := \int_0^t \int_0^T \mathcal{K}_{h_\sigma}(s-u)d(Y_\sigma - y)(s)du \text{ and}$$

$$\eta_\sigma(t) := \int_0^t \int_0^T \mathcal{K}_{h_\sigma}(s-u)dy(s)du - y(t) + x_0.$$

Convergence of the estimator: sketch of proof

- Inequality (14) and the Lipschitz continuity of C give

$$\sup_{t \in [0, T]} \mathbb{E}(\alpha_\sigma(t)^2 + \zeta_\sigma(t)^2) \leq \mathbf{c}\sigma^2 \quad (15)$$

and

$$\sup_{t \in [0, T]} \mathbb{E}(\beta_\sigma(t)^2 + \eta_\sigma(t)^2) \leq \mathbf{c}h_\sigma^2 \quad (16)$$

- Memin et al. (2001) gives

$$\sup_{t \in [0, T]} \mathbb{E}(\gamma_\sigma(t)^2) \leq \mathbf{c}\sigma^2 h_\sigma^{2H-2} \quad (17)$$

Asymptotic distribution: preliminaries

Assume that $C = [l(\cdot), u(\cdot)]$ with $l, u \in C^1([0, T], \mathbb{R})$.

For any $I : [0, T] \rightrightarrows \mathbb{R}$ such that $I(\cdot) \subset C(\cdot)$, consider

$$\mathcal{E}_I := \{t \in [0, T] : \exists \varepsilon > 0, \forall s \in]t - \varepsilon, t + \varepsilon[, x(s) \in I(s)\}.$$

Asymptotic distribution

For any $t \in \mathcal{E}_l \cup \mathcal{E}_u \cup \mathcal{E}_{\text{int}}(\mathcal{C})$,

$$\sigma^{-1/(2-H)}(\widehat{\tau}_\sigma(t) - \tau(t) - \gamma_\sigma(t)) \xrightarrow[\sigma \rightarrow 0]{\mathbb{L}^2} \mu(t) \quad (18)$$

and

$$\sigma^{-1/(2-H)}\dot{\gamma}_\sigma(t) \xrightarrow[\sigma \rightarrow 0]{\Delta} \mathcal{N}(0, \sigma_{H,\mathcal{K}}^2),$$

where

- $\mu(t) := (b(x(t)) - b(x(0)) + \dot{y}(t) - \dot{y}(0)) \int_A^B \mathcal{K}(u) u du.$
- $\sigma_{H,\mathcal{K}}^2 := H(2H - 1) \int_A^B \int_A^B |u - v|^{2H-2} \mathcal{K}(u) \mathcal{K}(v) du dv.$

Asymptotic distribution: sketch of proof

Steps:

1. By Inequality (15),

$$\sigma^{-1/(2-H)}(\alpha_\sigma(t) + \zeta_\sigma(t)) \xrightarrow[\sigma \rightarrow 0]{\mathbb{L}^2} 0.$$

2. Since $t \in \mathcal{E}_l \cup \mathcal{E}_u \cup \mathcal{E}_{\text{int}(\mathcal{C})}$, \dot{y} is continuous at time t and then

$$\sigma^{-1/(2-H)}(\beta_\sigma(t) + \eta_\sigma(t)) \xrightarrow[\sigma \rightarrow 0]{\mathbb{L}^2} \mu(t).$$

3. Since $\dot{\gamma}_\sigma(t)$ is defined by a Wiener integral,

$$\sigma^{-1/(2-H)}\dot{\gamma}_\sigma(t) \xrightarrow[\sigma \rightarrow 0]{\Delta} \mathcal{N}(0, \sigma_{\mathbb{H}, \mathcal{K}}^2).$$

Thank you for your attention!