



Adaptive step-size control for global approximation of SDEs driven by countably dimensional Wiener process

Łukasz Stępień

Faculty of Applied Mathematics, AGH University of Kraków

14th International Conference on Monte Carlo Methods and Applications - Paris, 30/06/2023



AGH Main references

- [1] P. Przybyłowicz, M. Sobieraj, Ł. Stępień, Efficient approximation of SDEs driven by countably dimensional Wiener process and Poisson random measure, *SIAM J. Numer. Anal.* 60 (2022), 824–855.
- [2] A. Kałuża, P. Przybyłowicz, Optimal global approximation of jump-diffusion SDEs via path-independent step-size control, *Appl. Numer. Math.* 128 (2018), 24–42.
- [3] N. Hofmann, T. Müller–Gronbach, K. Ritter, Optimal approximation of stochastic differential equations by adaptive step-size control, *Math. Comput.* 69 (1999), 1017–1034.
- [4] S.N. Cohen, R.J. Elliot, *Stochastic calculus and applications, 2nd ed.*, Probability and its applications, New York, Birkhäuser, 2015.
- [5] Ł. Stępień, Adaptive step-size control for global approximation of SDEs driven by countably dimensional Wiener process, preprint, March 2023, arXiv: 2303.13171



AGH Preliminaries - our model

- $(\Omega, \Sigma, (\Sigma_t)_{t \geq 0}, \mathbb{P})$ – probability space with sufficiently rich filtration,
- $T > 0$ – termination time,
- $W = [W_1, W_2, \dots]^T$ – countably dimensional Wiener process,
- $x_0 \in \mathbb{R}$ - initial value.

Let us consider the following one-dimensional SDE

$$X(t) = x_0 + \int_0^t a(s, X(s)) ds + \sum_{j=1}^{+\infty} \int_0^t \sigma_j(s) dW_j(s), \quad t \in [0, T], \quad (1)$$

where $\sigma(s) = (\sigma_1(s), \sigma_2(s), \dots) \in \ell^2(\mathbb{R})$ for each $s \in [0, T]$.



AGH Preliminaries - our model

- $(\Omega, \Sigma, (\Sigma_t)_{t \geq 0}, \mathbb{P})$ – probability space with sufficiently rich filtration,
- $T > 0$ – termination time,
- $W = [W_1, W_2, \dots]^T$ – countably dimensional Wiener process,
- $x_0 \in \mathbb{R}$ - initial value.

Let us consider the following one-dimensional SDE

$$X(t) = x_0 + \int_0^t a(s, X(s)) ds + \sum_{j=1}^{+\infty} \int_0^t \sigma_j(s) dW_j(s), \quad t \in [0, T], \quad (1)$$

where $\sigma(s) = (\sigma_1(s), \sigma_2(s), \dots) \in \ell^2(\mathbb{R})$ for each $s \in [0, T]$.



$\|\cdot\|_{\ell^2}$ - $\ell^2(\mathbb{R})$ norm;

$\|\cdot\|_2$ - L^2 norm on $\Omega \times [0, T]$.

Assumption (drift)

(A) We assume that the drift coefficient $a : [0, T] \times \mathbb{R} \mapsto \mathbb{R}$ belongs to $C^{1,2}([0, T] \times \mathbb{R})$ and satisfies the following conditions:

(A1) $|a(t, x) - a(s, x)| \leq C_1(1 + |x|)|t - s|$ for all $t, s \in [0, T]$, $x \in \mathbb{R}$,

(A2) $|a(t, 0)| \leq C_1$ for all $t \in [0, T]$,

(A3) $|a(t, x) - a(t, y)| \leq C_1|x - y|$ for all $x, y \in \mathbb{R}$, $t \in [0, T]$,

(A4) $\left| \frac{\partial a}{\partial x}(t, x) - \frac{\partial a}{\partial x}(t, y) \right| \leq C_1|x - y|$ for all pairs $(t, x), (t, y) \in [0, T] \times \mathbb{R}$
for some $C_1 > 0$.



Let $\delta = (\delta(k))_{k=1}^{\infty} \subset \mathbb{R}$ be a positive, strictly decreasing sequence vanishing at infinity.

By \mathcal{G}_{δ} we denote a set of all non-decreasing sequences $G = (G(n))_{n=1}^{\infty} \subset \mathbb{N}$ such that $G(n) \rightarrow +\infty$ and

$$\lim_{n \rightarrow +\infty} n^{1/2} \delta(G(n)) = 0. \quad (2)$$

The set of sequences G falling under (2) is non-empty.



Let $\delta = (\delta(k))_{k=1}^{\infty} \subset \mathbb{R}$ be a positive, strictly decreasing sequence vanishing at infinity.

By \mathcal{G}_{δ} we denote a set of all non-decreasing sequences $G = (G(n))_{n=1}^{\infty} \subset \mathbb{N}$ such that $G(n) \rightarrow +\infty$ and

$$\lim_{n \rightarrow +\infty} n^{1/2} \delta(G(n)) = 0. \quad (2)$$

The set of sequences G falling under (2) is non-empty.



Assumption (diffusion)

(S) We assume that diffusion coefficient $\sigma = (\sigma_1, \sigma_2, \dots) : [0, T] \mapsto \ell^2(\mathbb{R})$ satisfies the following conditions:

(S1) $\|\sigma(0)\|_{\ell^2} \leq C_2,$

(S2) $\|\sigma(t) - \sigma(s)\|_{\ell^2} \leq C_2|t - s|$ for all $t, s \in [0, T],$

(S3) $\|\sigma(t) - P_k\sigma(t)\|_{\ell^2} \leq C_2 \delta(k)$ for all $k \in \mathbb{N}, t \in [0, T].$

where $C_2 > 0,$ and $\delta = (\delta(k))_{k=1}^{+\infty}$ is as before.

Here we leverage the notation $P_k : \ell^2(\mathbb{R}) \mapsto \ell^2(\mathbb{R}),$ where $P_k x = (x_1, x_2, \dots, x_k, 0, 0, \dots).$ We denote $\sigma^k(t) = (P_k \sigma)(t)$ and $P_\infty = Id.$



AGH Truncated dimension approximation

Let $M \in \mathbb{N}$. Our idea is to provide the approximation of 'truncated' solution $X^M = (X^M(t))_{t \in [0, T]}$, defined as follows

$$X^M(t) = x_0 + \int_0^t a(s, X^M(s)) ds + \int_0^t \sigma^M(s) dW(s), \quad t \in [0, T], \quad (3)$$

where

$$\int_0^t \sigma^M(s) dW(s) = \sum_{j=1}^M \int_0^t \sigma_j(s) dW_j(s).$$



Proposition 1.

For every $M \in \mathbb{N} \cup \{\infty\}$ the equation (3) admits a unique strong solution $X = (X(t))_{t \in [0, T]}$. Moreover, there exists $K_1 \in (0, +\infty)$, such that for every $M \in \mathbb{N} \cup \{\infty\}$ we have that

$$\mathbb{E} \left(\sup_{0 \leq t \leq T} |X^M(t)|^2 \right) \leq K_1.$$

Proposition 2.

There exists $K_1 \in (0, +\infty)$ such that for any $M \in \mathbb{N}$ it holds

$$\sup_{0 \leq t \leq T} \|X(a, \sigma, x_0)(t) - X^M(a, \sigma, x_0)(t)\|_{L^2(\Omega)} \leq K_1 \delta(M).$$



AGH Minimal error bounds - definition of an admissible method

$\bar{X} = (\bar{X}_{M_n, \bar{k}_n})_{n=1}^\infty$ is defined by $\bar{X} = (\bar{M}, \bar{\Delta}, \bar{\mathcal{N}}, \bar{\phi})$, where:

- $\bar{M} = (M_n)_{n=1}^\infty \in \mathcal{G}_\delta$.
- $(\bar{\Delta}_n)_{n=1}^\infty$ is a sequence of (possibly) non-expanding partitions of the interval $[0, T]$

$$\bar{\Delta}_n: \quad 0 = \bar{t}_{0,n} < \bar{t}_{1,n} < \dots < \bar{t}_{\bar{k}_n-1,n} < \bar{t}_{\bar{k}_n,n} = T,$$

where for some $\bar{C}_1, \bar{C}_2 > 0$ it holds

$$\bar{C}_1 n \geq \bar{k}_n \geq \bar{C}_2 n^{1/2}, \quad n \geq n_0(\bar{X}) \in \mathbb{N}.$$

- $\bar{\mathcal{N}} = (\mathcal{N}_{M_n, \bar{k}_n}(W))_{n=1}^\infty$ is a sequence of information vectors

$$\mathcal{N}_{M_n, \bar{k}_n}(W) = \bigoplus_{k=1}^{M_n} [W_k(\bar{t}_{1,n}), W_k(\bar{t}_{2,n}), \dots, W_k(\bar{t}_{\bar{k}_n,n})].$$

- $\bar{\phi} = (\phi_n)_{n=1}^\infty$ is a sequence of Borel mappings $\phi_n: \mathbb{R}^{n \cdot M_n} \mapsto L^2([0, T])$, such that

$$\phi_n(\mathcal{N}_{M_n, \bar{k}_n}(W)) = \bar{X}_{M_n, \bar{k}_n}, \quad n \in \mathbb{N}.$$



AGH Minimal error bounds - definition of an admissible method

$\bar{X} = (\bar{X}_{M_n, \bar{k}_n})_{n=1}^\infty$ is defined by $\bar{X} = (\bar{M}, \bar{\Delta}, \bar{\mathcal{N}}, \bar{\phi})$, where:

- $\bar{M} = (M_n)_{n=1}^\infty \in \mathcal{G}_\delta$.
- $(\bar{\Delta}_n)_{n=1}^\infty$ is a sequence of (possibly) non-expanding partitions of the interval $[0, T]$

$$\bar{\Delta}_n: \quad 0 = \bar{t}_{0,n} < \bar{t}_{1,n} < \dots < \bar{t}_{\bar{k}_n-1,n} < \bar{t}_{\bar{k}_n,n} = T,$$

where for some $\bar{C}_1, \bar{C}_2 > 0$ it holds

$$\bar{C}_1 n \geq \bar{k}_n \geq \bar{C}_2 n^{1/2}, \quad n \geq n_0(\bar{X}) \in \mathbb{N}.$$

- $\bar{\mathcal{N}} = (\mathcal{N}_{M_n, \bar{k}_n}(W))_{n=1}^\infty$ is a sequence of information vectors

$$\mathcal{N}_{M_n, \bar{k}_n}(W) = \bigoplus_{k=1}^{M_n} [W_k(\bar{t}_{1,n}), W_k(\bar{t}_{2,n}), \dots, W_k(\bar{t}_{\bar{k}_n,n})].$$

- $\bar{\phi} = (\phi_n)_{n=1}^\infty$ is a sequence of Borel mappings $\phi_n: \mathbb{R}^{n \cdot M_n} \mapsto L^2([0, T])$, such that

$$\phi_n(\mathcal{N}_{M_n, \bar{k}_n}(W)) = \bar{X}_{M_n, \bar{k}_n}, \quad n \in \mathbb{N}.$$



AGH Minimal error bounds - definition of an admissible method

$\bar{X} = (\bar{X}_{M_n, \bar{k}_n})_{n=1}^\infty$ is defined by $\bar{X} = (\bar{M}, \bar{\Delta}, \bar{\mathcal{N}}, \bar{\phi})$, where:

- $\bar{M} = (M_n)_{n=1}^\infty \in \mathcal{G}_\delta$.
- $(\bar{\Delta}_n)_{n=1}^\infty$ is a sequence of (possibly) non-expanding partitions of the interval $[0, T]$

$$\bar{\Delta}_n: \quad 0 = \bar{t}_{0,n} < \bar{t}_{1,n} < \dots < \bar{t}_{\bar{k}_n-1,n} < \bar{t}_{\bar{k}_n,n} = T,$$

where for some $\bar{C}_1, \bar{C}_2 > 0$ it holds

$$\bar{C}_1 n \geq \bar{k}_n \geq \bar{C}_2 n^{1/2}, \quad n \geq n_0(\bar{X}) \in \mathbb{N}.$$

- $\bar{\mathcal{N}} = (\mathcal{N}_{M_n, \bar{k}_n}(W))_{n=1}^\infty$ is a sequence of information vectors

$$\mathcal{N}_{M_n, \bar{k}_n}(W) = \bigoplus_{k=1}^{M_n} [W_k(\bar{t}_{1,n}), W_k(\bar{t}_{2,n}), \dots, W_k(\bar{t}_{\bar{k}_n,n})].$$

- $\bar{\phi} = (\phi_n)_{n=1}^\infty$ is a sequence of Borel mappings $\phi_n: \mathbb{R}^{n \cdot M_n} \mapsto L^2([0, T])$, such that

$$\phi_n(\mathcal{N}_{M_n, \bar{k}_n}(W)) = \bar{X}_{M_n, \bar{k}_n}, \quad n \in \mathbb{N}.$$



AGH Minimal error bounds - definition of an admissible method

$\bar{X} = (\bar{X}_{M_n, \bar{k}_n})_{n=1}^\infty$ is defined by $\bar{X} = (\bar{M}, \bar{\Delta}, \bar{\mathcal{N}}, \bar{\phi})$, where:

- $\bar{M} = (M_n)_{n=1}^\infty \in \mathcal{G}_\delta$.
- $(\bar{\Delta}_n)_{n=1}^\infty$ is a sequence of (possibly) non-expanding partitions of the interval $[0, T]$

$$\bar{\Delta}_n: \quad 0 = \bar{t}_{0,n} < \bar{t}_{1,n} < \dots < \bar{t}_{\bar{k}_n-1,n} < \bar{t}_{\bar{k}_n,n} = T,$$

where for some $\bar{C}_1, \bar{C}_2 > 0$ it holds

$$\bar{C}_1 n \geq \bar{k}_n \geq \bar{C}_2 n^{1/2}, \quad n \geq n_0(\bar{X}) \in \mathbb{N}.$$

- $\bar{\mathcal{N}} = (\mathcal{N}_{M_n, \bar{k}_n}(W))_{n=1}^\infty$ is a sequence of information vectors

$$\mathcal{N}_{M_n, \bar{k}_n}(W) = \bigoplus_{k=1}^{M_n} [W_k(\bar{t}_{1,n}), W_k(\bar{t}_{2,n}), \dots, W_k(\bar{t}_{\bar{k}_n,n})].$$

- $\bar{\phi} = (\phi_n)_{n=1}^\infty$ is a sequence of Borel mappings $\phi_n: \mathbb{R}^{n \cdot M_n} \mapsto L^2([0, T])$, such that

$$\phi_n(\mathcal{N}_{M_n, \bar{k}_n}(W)) = \bar{X}_{M_n, \bar{k}_n}, \quad n \in \mathbb{N}.$$



AGH Minimal error bounds - definition of an admissible method

$\bar{X} = (\bar{X}_{M_n, \bar{k}_n})_{n=1}^\infty$ is defined by $\bar{X} = (\bar{M}, \bar{\Delta}, \bar{\mathcal{N}}, \bar{\phi})$, where:

- $\bar{M} = (M_n)_{n=1}^\infty \in \mathcal{G}_\delta$.
- $(\bar{\Delta}_n)_{n=1}^\infty$ is a sequence of (possibly) non-expanding partitions of the interval $[0, T]$

$$\bar{\Delta}_n: \quad 0 = \bar{t}_{0,n} < \bar{t}_{1,n} < \dots < \bar{t}_{\bar{k}_n-1,n} < \bar{t}_{\bar{k}_n,n} = T,$$

where for some $\bar{C}_1, \bar{C}_2 > 0$ it holds

$$\bar{C}_1 n \geq \bar{k}_n \geq \bar{C}_2 n^{1/2}, \quad n \geq n_0(\bar{X}) \in \mathbb{N}.$$

- $\bar{\mathcal{N}} = (\mathcal{N}_{M_n, \bar{k}_n}(W))_{n=1}^\infty$ is a sequence of information vectors

$$\mathcal{N}_{M_n, \bar{k}_n}(W) = \bigoplus_{k=1}^{M_n} [W_k(\bar{t}_{1,n}), W_k(\bar{t}_{2,n}), \dots, W_k(\bar{t}_{\bar{k}_n,n})].$$

- $\bar{\phi} = (\phi_n)_{n=1}^\infty$ is a sequence of Borel mappings $\phi_n: \mathbb{R}^{n \cdot M_n} \mapsto L^2([0, T])$, such that

$$\phi_n(\mathcal{N}_{M_n, \bar{k}_n}(W)) = \bar{X}_{M_n, \bar{k}_n}, \quad n \in \mathbb{N}.$$



AGH Minimal error bounds - admissible algorithms

The class of algorithms satisfying above conditions is denoted by χ_{noneq} . We also distinguish a subclass $\chi_{eq} \subset \chi_{noneq}$ of methods leveraging equidistant partitions

$$\chi_{eq} = \{\bar{X} \in \chi_{noneq} \mid \exists_{n_0=n_0(\bar{X})} : \forall_{n \geq n_0} \bar{\Delta}_n = \{jT/n : j = 0, 1, \dots, \bar{k}_n\}\}.$$

Similarly, for a fixed truncation sequence \bar{M} , we define corresponding subclasses $\chi_{noneq}^{\bar{M}}$ and $\chi_{eq}^{\bar{M}}$.



AGH Minimal error bounds - cont'd

Informational cost of the algorithm \bar{X}_{M_n, \bar{k}_n} :

$$\text{cost}(\bar{X}_{M_n, \bar{k}_n}) = \begin{cases} M_n \cdot \bar{k}_n, & \text{when } \sigma \neq 0, \\ 0, & \text{when } \sigma \equiv 0. \end{cases}$$

Global approximation error for \bar{X}_{M_n, \bar{k}_n} :

$$\|X - \bar{X}_{M_n, \bar{k}_n}\|_2 = \left(\mathbb{E} \int_0^T |X(t) - \bar{X}_{M_n, \bar{k}_n}(t)|^2 dt \right)^{1/2}, \quad n \in \mathbb{N}.$$



AGH Minimal error bounds - cont'd

Informational cost of the algorithm \bar{X}_{M_n, \bar{k}_n} :

$$\text{cost}(\bar{X}_{M_n, \bar{k}_n}) = \begin{cases} M_n \cdot \bar{k}_n, & \text{when } \sigma \neq 0, \\ 0, & \text{when } \sigma \equiv 0. \end{cases}$$

Global approximation error for \bar{X}_{M_n, \bar{k}_n} :

$$\|X - \bar{X}_{M_n, \bar{k}_n}\|_2 = \left(\mathbb{E} \int_0^T |X(t) - \bar{X}_{M_n, \bar{k}_n}(t)|^2 dt \right)^{1/2}, \quad n \in \mathbb{N}.$$



AGH Minimal error bounds - notation

Let $(a(n))_{n=1}^{\infty}, (b(n))_{n=1}^{\infty}$ be two sequences of positive numbers.

$$a(n) \approx b(n) \quad :\Leftrightarrow \quad \lim_{n \rightarrow +\infty} \frac{a(n)}{b(n)} = 1.$$

Furthermore, we will say that

$$a(n) \lesssim b(n) \quad :\Leftrightarrow \quad \limsup_{n \rightarrow +\infty} \frac{a(n)}{b(n)} \leq 1.$$



Theorem 2 (S., 2023), part 1.

Let $\bar{M} = (M_n)_{n=1}^\infty \in \mathcal{G}_\delta$. We have the following asymptotic bound

$$\inf_{\bar{X} \in \mathcal{X}_{noneq}^{\bar{M}}} (\text{cost}(\bar{X}_{M_n, \bar{k}_n}))^{1/2} \|\bar{X}_{M_n, \bar{k}_n} - X\|_2 \gtrsim \frac{M_n^{1/2}}{\sqrt{6}} \int_0^T \|\sigma(t)\|_{\ell^2} dt.$$

Theorem 2 (S., 2023), part 2.

Let $\bar{M} = (M_n)_{n=1}^\infty \in \mathcal{G}_\delta$. We have the following asymptotic bound

$$\inf_{\bar{X} \in \mathcal{X}_{eq}^{\bar{M}}} (\text{cost}(\bar{X}_{M_n, \bar{k}_n}))^{1/2} \|\bar{X}_{M_n, \bar{k}_n} - X\|_2 \gtrsim M_n^{1/2} \sqrt{\frac{T}{6}} \left(\int_0^T \|\sigma(t)\|_{\ell^2}^2 dt \right)^{1/2}.$$



Theorem 2 (S., 2023), part 1.

Let $\bar{M} = (M_n)_{n=1}^\infty \in \mathcal{G}_\delta$. We have the following asymptotic bound

$$\inf_{\bar{X} \in \mathcal{X}_{noneq}^{\bar{M}}} (\text{cost}(\bar{X}_{M_n, \bar{k}_n}))^{1/2} \|\bar{X}_{M_n, \bar{k}_n} - X\|_2 \gtrsim \frac{M_n^{1/2}}{\sqrt{6}} \int_0^T \|\sigma(t)\|_{\ell^2} dt.$$

Theorem 2 (S., 2023), part 2.

Let $\bar{M} = (M_n)_{n=1}^\infty \in \mathcal{G}_\delta$. We have the following asymptotic bound

$$\inf_{\bar{X} \in \mathcal{X}_{eq}^{\bar{M}}} (\text{cost}(\bar{X}_{M_n, \bar{k}_n}))^{1/2} \|\bar{X}_{M_n, \bar{k}_n} - X\|_2 \gtrsim M_n^{1/2} \sqrt{\frac{T}{6}} \left(\int_0^T \|\sigma(t)\|_{\ell^2}^2 dt \right)^{1/2}.$$



Let us denote by

$$C_{noneq} = \frac{1}{\sqrt{6}} \int_0^T \|\sigma(t)\|_{\ell^2} dt$$

and

$$C_{eq} = \sqrt{\frac{T}{6}} \left(\int_0^T \|\sigma(t)\|_{\ell^2}^2 dt \right)^{1/2}$$

the constants appearing on the RHS in Theorem 2, respectively.



AGH Investigation of optimal algorithm in $\chi_{eq}^{\bar{M}}$ - cont'd

We show that

$$n^{1/2} \|X - X_{M_n^*, n}^{Eq*}\|_2 \approx \left(\frac{T}{6} \sum_{j=0}^{n-1} \|\sigma^{M_n^*}(t_{j,n}^{eq})\|_{\ell^2}^2 \frac{T}{n} \right)^{1/2}, \quad n \rightarrow +\infty.$$

As a result,

$$(M_n^*)^{1/2} \|X - X_{M_n^*, n}^{Eq*}\|_2 \approx (M_n^*)^{1/2} \sqrt{\frac{T}{6}} \left(\int_0^T \|\sigma(t)\|_{\ell^2}^2 dt \right)^{1/2}, \quad n \rightarrow +\infty.$$



AGH Algorithm with adaptive step-size control

Let us fix $n \in \mathbb{N}$ and $\bar{M} = (M_n^*)_{n=1}^\infty \in \mathcal{G}_\delta$. The proposed scheme $X_{M_n^*, k_n^*}^{\text{step}}$ uses the following adaptive path-independent step-size control: $\hat{t}_{0,n} := 0$ and

$$\hat{t}_{j+1,n} := \hat{t}_{j,n} + \frac{T}{n \max\{\varepsilon_n, \|\sigma^{M_n^*}(\hat{t}_{j,n})\|_{\ell^2}\}}, \quad j = 0, 1, \dots, k_n^* - 1,$$

where $k_n^* = \inf\{j \in \mathbb{N} \mid \hat{t}_{j,n} \geq T\}$, and $\bar{\varepsilon} = (\varepsilon_n)_{n=1}^\infty \subset \mathbb{R}_+$ is a non-increasing sequence satisfying

$$\lim_{n \rightarrow +\infty} \varepsilon_n = \lim_{n \rightarrow +\infty} \frac{1}{n \varepsilon_n^2} = 0.$$



AGH Algorithm with adaptive step-size - cont'd

We introduce the partition Δ_n^* by taking $t_{j,n}^* = \hat{t}_{j,n}$, $j = 0, 1, \dots, k_n^* - 1$, and $t_{k_n^*,n}^* = T$.

Ultimately, for each j , we perform linear interpolation between $X_{M_n^*, k_n^*}^{step}(t_{j,n}^*)$ and $X_{M_n^*, k_n^*}^{step}(t_{j+1,n}^*)$ to obtain the final process

$$X_{M_n^*, k_n^*}^* = (X_{M_n^*, k_n^*}^{step}(t))_{t \in [0, T]}.$$

Properties

Under the assumptions (A1) - (A4), (S1)-(S3):

- The proposed method $X_{M_n^*, k_n^*}^{step}$ with step-size control is an element of χ_{noneq} and attains point T .
- k_n^* is deterministic and $\lim_{n \rightarrow +\infty} k_n^*(\sigma) = +\infty$;
- $\max_{0 \leq j \leq k_n^* - 1} (t_{j+1,n}^* - t_{j,n}^*) \leq \frac{T}{n\varepsilon_n} \rightarrow 0$, $n \rightarrow +\infty$.



AGH Algorithm with adaptive step-size - cont'd

We introduce the partition Δ_n^* by taking $t_{j,n}^* = \hat{t}_{j,n}$, $j = 0, 1, \dots, k_n^* - 1$, and $t_{k_n^*,n}^* = T$.

Ultimately, for each j , we perform linear interpolation between $X_{M_n^*, k_n^*}^{step}(t_{j,n}^*)$ and $X_{M_n^*, k_n^*}^{step}(t_{j+1,n}^*)$ to obtain the final process

$$X_{M_n^*, k_n^*}^* = (X_{M_n^*, k_n^*}^{step}(t))_{t \in [0, T]}.$$

Properties

Under the assumptions (A1) - (A4), (S1)-(S3):

- The proposed method $X_{M_n^*, k_n^*}^{step}$ with step-size control is an element of χ_{noneq} and attains point T .
- k_n^* is deterministic and $\lim_{n \rightarrow +\infty} k_n^*(\sigma) = +\infty$;
- $\max_{0 \leq j \leq k_n^* - 1} (t_{j+1,n}^* - t_{j,n}^*) \leq \frac{T}{n \varepsilon_n} \rightarrow 0$, $n \rightarrow +\infty$.

Recall that by \mathcal{G}_δ we denote a set of all non-decreasing sequences $G = (G(n))_{n=1}^\infty \subset \mathbb{N}$ such that $G(n) \rightarrow +\infty$ and

$$\lim_{n \rightarrow +\infty} n^{1/2} \delta(G(n)) = 0.$$

Theorem 3. (S. 2023)

Let a, σ satisfy conditions (A) and (S) with sequence δ , respectively. Then, for every method $\bar{X} = (\bar{X}_{M_n, \bar{k}_n})_{n=1}^\infty \in \chi_\diamond, \diamond \in \{noneq, eq\}$, we have

$$\left(\text{cost}(\bar{X}_{M_n, \bar{k}_n})\right)^{1/2} \left\| X - \bar{X}_{M_n, \bar{k}_n} \right\|_2 \gtrsim \left(\delta^{-1}(n^{-1/2})\right)^{1/2} C_\diamond, \quad n \rightarrow +\infty.$$

**Theorem 3. (S. 2023) - part 2.**

For every truncation level sequence M_n with $\delta^{-1}(n^{-1/2}) = o(M_n), n \rightarrow +\infty$, there exists a sequence $M^* = (M_n^*)_{n=1}^\infty \in \mathcal{G}_\delta$ such that $M_n^* = o(M_n), n \rightarrow +\infty$, and:

a) the truncated-dimension Euler algorithm with adaptive path-independent step-size control $X^* = (X_{M_n^*, k_n^*}^*)_{n=1}^\infty \in \chi_{noneq}$ satisfying

$$\left(\text{cost}(\bar{X}_{M_n^*, k_n^*})\right)^{1/2} \|X - \bar{X}_{M_n^*, k_n^*}\|_2 \lesssim \sqrt{\frac{M_n^*}{6}} \int_0^T \|\sigma(t)\|_{\ell^2} dt, \quad n \rightarrow +\infty;$$

b) the truncated-dimension Euler algorithm $X^{Eq*} = (X_{M_n^*, n}^{Eq*})_{n=1}^\infty \in \chi_{eq}$, based on the sequence of equidistant meshes, and satisfying

$$\left(\text{cost}(X_{M_n^*, n}^{Eq*})\right)^{1/2} \|X - X_{M_n^*, n}^{Eq*}\|_2 \lesssim \sqrt{\frac{M_n^* T}{6}} \left(\int_0^T \|\sigma(t)\|_{\ell^2}^2 dt\right)^{1/2}, \quad n \rightarrow +\infty.$$



AGH Numerical experiments - chosen model

$$a(t, x) = (t + 2)(x - 1), \quad t \in [0, T], \quad x \in \mathbb{R},$$

$$\sigma_k(t) = \frac{e^{2t} + 2}{(k + 1)^p \sqrt{\log(k + 1)}} \quad t \in [0, T], \quad k = 1, 2, \dots,$$

where $p > 1/2$.

For all $l \in \mathbb{N}$, $l > 1$ it holds

$$\|\sigma(t) - P_l \sigma(t)\|_{\ell^2}^2 = \left| \sum_{k=l}^{+\infty} \frac{(e^{2t} + 2)^2}{(k + 1)^{2p} \log(k + 1)} \right| \leq (e^{2T} + 2)^2 \left| \int_{(2p-1)\log(l+1)}^{+\infty} e^{-v} v^{-1} dv \right|,$$

and the integral appearing above is equal to the upper incomplete gamma function $\Gamma(1, (2p - 1) \log(l + 1))$. Therefore,

$$\|\sigma(t) - P_l \sigma(t)\|_{\ell^2} \leq (e^{2T} + 2) e^{-0.5(2p-1)\log(l+1)} = (e^{2T} + 2) (l + 1)^{1/2-p}, \quad l \in \mathbb{N}.$$



$$\|\sigma(t) - P_n\sigma(t)\|_{\ell^2} \leq K(T)n^{1/2-p}, \quad n \in \mathbb{N}.$$

Therefore, we can assume

$$\delta(n) \approx n^{1/2-p} \quad \Rightarrow \quad \delta^{-1}(n^{-1/2}) \approx n^{\frac{1}{2p-1}}.$$

In our simulations, we set $x_0 = 0.9$, $T = 1.5$, $p = 0.9$, hence the admissible truncation levels can be of the form

$$\mathcal{G}_\delta \ni M_n \gtrsim n^{5/4+\varepsilon}, \quad n \rightarrow +\infty,$$

for some $\varepsilon > 0$. Our final choice is to take $M_n^* = 0.15 \cdot n^{1.28}$ and $\varepsilon_n = n^{-0.3}$, $n \in \mathbb{N}$.

We also note that $C_{eq} = 4.550580\dots$, while $C_{noneq} = 3.873137\dots$



$$\|\sigma(t) - P_n\sigma(t)\|_{\ell^2} \leq K(T)n^{1/2-p}, \quad n \in \mathbb{N}.$$

Therefore, we can assume

$$\delta(n) \approx n^{1/2-p} \quad \Rightarrow \quad \delta^{-1}(n^{-1/2}) \approx n^{\frac{1}{2p-1}}.$$

In our simulations, we set $x_0 = 0.9$, $T = 1.5$, $p = 0.9$, hence the admissible truncation levels can be of the form

$$\mathcal{G}_\delta \ni M_n \gtrsim n^{5/4+\varepsilon}, \quad n \rightarrow +\infty,$$

for some $\varepsilon > 0$. Our final choice is to take $M_n^* = 0.15 \cdot n^{1.28}$ and $\varepsilon_n = n^{-0.3}$, $n \in \mathbb{N}$.

We also note that $C_{eq} = 4.550580\dots$, while $C_{noneq} = 3.873137\dots$



$$\|\sigma(t) - P_n\sigma(t)\|_{\ell^2} \leq K(T)n^{1/2-p}, \quad n \in \mathbb{N}.$$

Therefore, we can assume

$$\delta(n) \approx n^{1/2-p} \quad \Rightarrow \quad \delta^{-1}(n^{-1/2}) \approx n^{\frac{1}{2p-1}}.$$

In our simulations, we set $x_0 = 0.9$, $T = 1.5$, $p = 0.9$, hence the admissible truncation levels can be of the form

$$\mathcal{G}_\delta \ni M_n \gtrsim n^{5/4+\varepsilon}, \quad n \rightarrow +\infty,$$

for some $\varepsilon > 0$. Our final choice is to take $M_n^* = 0.15 \cdot n^{1.28}$ and

$$\varepsilon_n = n^{-0.3}, \quad n \in \mathbb{N}.$$

We also note that $C_{eq} = 4.550580\dots$, while $C_{noneq} = 3.873137\dots$



AGH Numerical experiments - cont'd

Our target is to verify if the empirical ratio $\hat{C}_{noneq}/\hat{C}_{eq}$ matches the theoretical one (0.8511). To this end, we leverage the following metric

$$\text{error}(X^{alg}) := \left(\frac{1}{K} \sum_{l=1}^K \mathcal{Q} \left(|X_l^{alg}(a, b, W^{(l)}) - X_{W_{ratio}M_n^*, n^*, l}(a, b, W^{(l)})|^2 \right) \right)^{1/2},$$

where:

- K is a number of simulated trajectories;
- X_l^{alg} , $X_{W_{ratio}M_n^*, n^*, l}$, and $W^{(l)}$ are the l -th generated trajectories of the corresponding processes $X^{alg} \in \{X_{M_n^*, k_n^*}^{Eq*}, X_{M_n^*, k_n^*}^{step}\}$, $l = 1, \dots, K$;
- \mathcal{Q} is a composite Simpson quadrature based on: the time points for which X^{alg} is evaluated, and the midpoints of the corresponding subintervals;
- rare-fine grid approach is utilised due to the fact that the exact solution formula contains stochastic integrals. The fine grid method is always based on $MAX_n = 10^6$ equidistant nodes and uses $W_{ratio} \cdot M_n^*$ - dimensional Wiener process.

n	k_n^*	M_n^*	K	W_{ratio}	Improvement ratio
1000	7832	1037	1000	2.0	0.977977
2000	15686	2520	1000	2.0	0.945800
5000	39249	8142	250	1.5	0.915620
10000	78520	19773	94	1.5	0.976337

Table: Simulation results for $X_{M_n^*, n}^{Eq^*}$ and $X_{M_n^*, k_n^*}^{step}$.



- We constructed truncated dimension Euler schemes: a) based on equidistant mesh; b) with adaptive step-size control; in a model with additive, countably dimensional structure of noise.
- We derived lower bound for the exact asymptotic error behaviour. Those estimates show that in order to decrease the minimal error, a significant additional cost needs to be taken.
- We proved that constructed methods are optimal / almost optimal in the considered (sub)classes.
- the conclusions from our experiments seem to be in line with the derived theoretical results.



- We constructed truncated dimension Euler schemes: a) based on equidistant mesh; b) with adaptive step-size control; in a model with additive, countably dimensional structure of noise.
- We derived lower bound for the exact asymptotic error behaviour. Those estimates show that in order to decrease the minimal error, a significant additional cost needs to be taken.
- We proved that constructed methods are optimal / almost optimal in the considered (sub)classes.
- the conclusions from our experiments seem to be in line with the derived theoretical results.



AGH

Summary and conclusions

- We constructed truncated dimension Euler schemes: a) based on equidistant mesh; b) with adaptive step-size control; in a model with additive, countably dimensional structure of noise.
- We derived lower bound for the exact asymptotic error behaviour. Those estimates show that in order to decrease the minimal error, a significant additional cost needs to be taken.
- We proved that constructed methods are optimal / almost optimal in the considered (sub)classes.
- the conclusions from our experiments seem to be in line with the derived theoretical results.



- We constructed truncated dimension Euler schemes: a) based on equidistant mesh; b) with adaptive step-size control; in a model with additive, countably dimensional structure of noise.
- We derived lower bound for the exact asymptotic error behaviour. Those estimates show that in order to decrease the minimal error, a significant additional cost needs to be taken.
- We proved that constructed methods are optimal / almost optimal in the considered (sub)classes.
- the conclusions from our experiments seem to be in line with the derived theoretical results.



- We constructed truncated dimension Euler schemes: a) based on equidistant mesh; b) with adaptive step-size control; in a model with additive, countably dimensional structure of noise.
- We derived lower bound for the exact asymptotic error behaviour. Those estimates show that in order to decrease the minimal error, a significant additional cost needs to be taken.
- We proved that constructed methods are optimal / almost optimal in the considered (sub)classes.
- the conclusions from our experiments seem to be in line with the derived theoretical results.

- Considering algorithms with additional adaptation with respect to the Wiener process coordinates,
- Extending present results linked to global approximation problem to the models with $\sigma = \sigma(t, x)$ and possibly jumps,
- Case study - efficient implementation of constructed algorithms by using GPU computational power.

Thank you for your attention!