

Principles of stochastic geometric numerical integration

Part I: nonlinear stability analysis

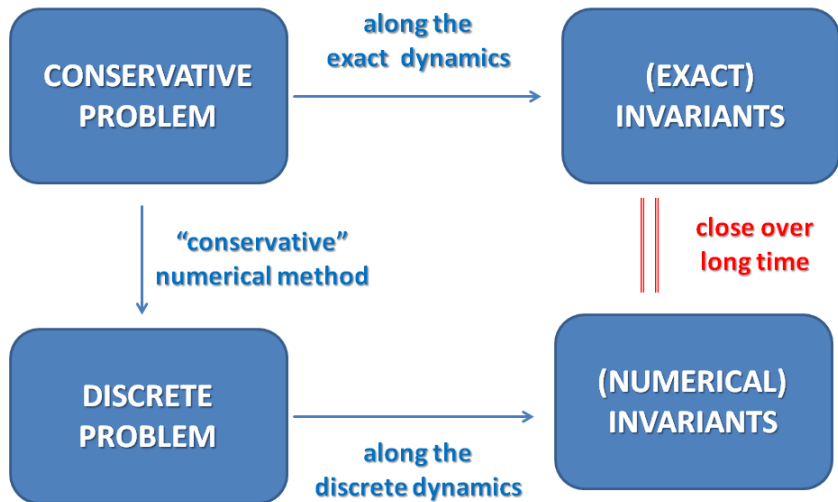
Raffaele D'Ambrosio

DISIM - *University of L'Aquila*

Gran Sasso Science Institute

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The numerics of preserving structures



Geometric numerical integration

- The denomination recalls the approach to geometry formulated by **Felix Klein** in his Erlangen program (1893);
- **geometry** = the study of **invariants** under certain transformations;
- geometric numerical methods launched to retain peculiar features of dynamical systems **under discretizations**;
- Arnold (2002), speech addressed to the participants of the International Congress of Mathematicians in Beijing:

“The design of stable discretizations of systems of PDEs often hinges on capturing subtle aspects of the structure of the system in the discretization. This new geometric viewpoint has provided a unifying understanding of a variety of innovative numerical methods developed over recent decades”;

Geometric numerical integration (ctd.)

- subtle connection with the so-called *geometric integration theory* by Hassler Whitney (1957);
- Arnold shows that the function spaces introduced by Whitney (the so-called **Whitney elements**) represent what is required for a geometric discretization of many PDEs.



Douglas N. Arnold, Differential complexes and numerical stability, Proceedings of the ICM, Beijing 2002, vol. 1, 137–157 (2002).



R. McLachlan, Featured Review: Geometric Numerical Integration: Structure-Preserving Algorithms for Ordinary Differential Equations. SIAM Review 45(4), 817–821 (2003).



E. Hairer, C. Lubich, G. Wanner, Geometric numerical integration. Structure-preserving algorithms for ordinary differential equations, Second edition, Springer Series in Computational Mathematics 31, Springer-Verlag, Berlin (2006).



E. Hairer, G. Wanner, Geometric numerical integration illustrated by the Störmer-Verlet method, Acta Numer. 12, 399–450 (2003).

Geometric numerical integration (ctd.)

A famous method: **leapfrog method**, also known as **Störmer-Verlet** method. This method, for the discretization of the second order problem

$$\ddot{q} = f(q),$$

is given by

$$q_{n+1} - 2q_n + q_{n-1} = h^2 f(q_n).$$

Extensively used in many fields, such as celestial mechanics and molecular dynamics.

- First due to **Störmer** (1907), a variant of this scheme to compute the motion of ionized particles in the Earth's magnetic field (aurora borealis);
- above formulation due to **Verlet** (1967) for the computer simulation of molecular dynamics models;
- interested in the history of science, he discovered that his scheme was previously used by several authors: for instance, by **Newton** in his Principia (1687), to prove Kepler's second law.

Geometric numerical integration (ctd.)

- Seminal contribution by **De Vogelaere** (1956), “*a marvellous paper, short, clear, elegant, written in one week, submitted for publication and never published*”;
- examples of numerical methods (such as the symplectic Euler method) retaining the symplecticity of Hamiltonian problems;
- still regarding Hamiltonian problems, successive contributions by **Ruth** (1983) and **Kang** (1985);
- **1988** starting year for the establishment of a theory of conservative numerics for Hamiltonian problems: criterion for the numerical conservation of the symplecticity via Runge-Kutta methods independently by **Lasagni**, **Sanz-Serna**, **Suris**, depending on a similar condition discovered by **Cooper** (1987) for the numerical conservation of quadratic first integrals.



R. D'Ambrosio, *Numerical approximation of differential problems*, Springer, to appear.

Geometric numerical integration: applications

- **Hamiltonian** dynamics;
- **Molecular dynamics** is a rich source of applications for geometric integration;
- **weather** prediction;
- **robotics**;
- study of the **Schrödinger equation** and statistical mechanics.



N. Bou-Rabee, J. M. Sanz-Serna, *Geometric integrators and the Hamiltonian Monte Carlo method*, Acta Numerica 27, 113–206 (2018).



M. Fernandez-Pendas, E. Akhmatkaya, J. M. Sanz-Serna, *Adaptive multi-stage integrators for optimal energy conservation in molecular simulations*, J. Comp. Phys. 327, 434–449 (2016).



B.J. Leimkuhler, S. Reich, *Simulating Hamiltonian dynamics*, Cambridge University Press (2004).

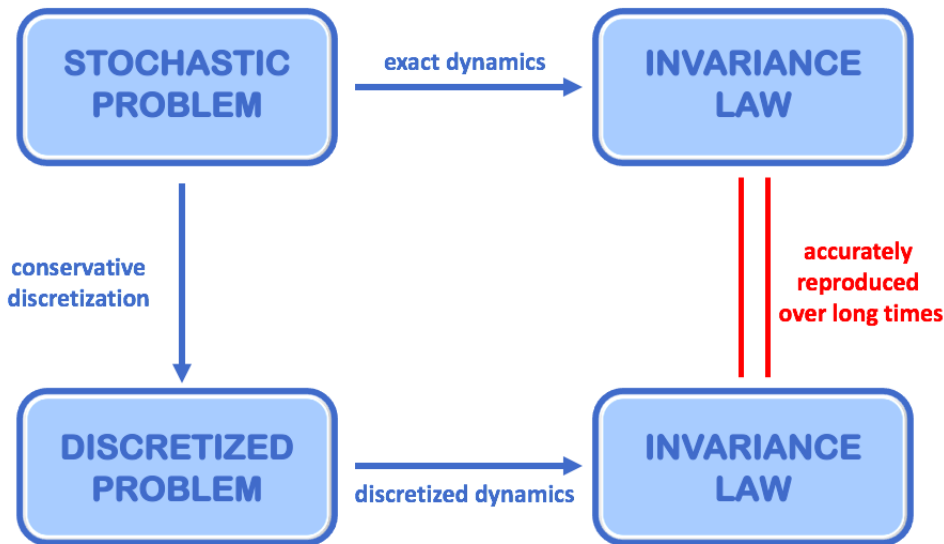


R. McLachlan, *Symplectic integration of Hamiltonian wave equations*, Numer. Math. 66(1), 465–492 (1993).



M.Q. Zhang, *Explicit unitary schemes to solve quantum operator equations of motion*, J. Stat. Phys. 65(3), 793–799 (1991).

Stochastic geometric numerical integration



Nonlinear SDEs

Retaining dissipativity of stochastic differential equations



E. Buckwar, R. D'Ambrosio, *Exponential mean-square stability properties of stochastic linear multistep methods*, submitted.



R. D'Ambrosio, S. Di Giovacchino, *Mean-square contractivity of stochastic theta-methods*, *Comm. Nonlin. Sci. Numer. Simul.* 96, article number 105671 (2021).



R. D'Ambrosio, S. Di Giovacchino, *Nonlinear stability issues for stochastic Runge-Kutta methods*, *Comm. Nonlin. Sci. Numer. Simul.* 94, article number 105549 (2021).



R. D'Ambrosio, S. Di Giovacchino, *Optimal ϑ -methods for mean-square dissipative stochastic differential equations*, submitted.



D.J. Higham, P.E. Kloeden, *Numerical methods for nonlinear stochastic differential equations with jumps*, *Numer. Math.* (2005).

Memorandum on nonlinear deterministic equations

Consider a nonlinear test problem

$$\begin{cases} y'(t) = \varphi(t, y(t)), & t \geq 0, \\ y(0) = y_0, \end{cases}$$

with $\varphi : \mathbb{R} \times \mathbb{R}^m \rightarrow \mathbb{R}^m$ satisfying a one-sided Lipschitz condition

$$(\varphi(t, y_1) - \varphi(t, y_2))^\top (y_1 - y_2) \leq 0, \quad (\star)$$

for all $t \geq 0$ and $y_1, y_2 \in \mathbb{R}^m$. Denote by $y(t)$ and $\tilde{y}(t)$ two solutions with initial conditions y_0 and \tilde{y}_0 , respectively. Condition (\star) implies the **contractivity** of the trajectories

$$\|y(t_2) - \tilde{y}(t_2)\| \leq \|y(t_1) - \tilde{y}(t_1)\|,$$

for $0 \leq t_1 \leq t_2$, where $\|\cdot\|$ is any norm in \mathbb{R}^m , and the corresponding problem is said to be **dissipative**.

Contractive numerical solutions for dissipative problems: AN-stability, G-stability, algebraic stability, ... (pioneered by Dahlquist, 1975).

Stochastic contractivity

Nonlinear Itô problem:

$$dX(t) = f(X(t))dt + g(X(t))dW(t), \quad t \in [0, T]$$

Assumptions

(i) \mathcal{C}^1 -continuity of drift and diffusion;

(ii) **one-sided Lipschitz condition** for the drift

$$\langle x - y, f(x) - f(y) \rangle \leq \mu \|x - y\|^2, \quad \forall x, y \in \mathbb{R}^n;$$

(iii) **global Lipschitz** for the diffusion

$$\|g(x) - g(y)\|^2 \leq L \|x - y\|^2, \quad \forall x, y \in \mathbb{R}^n.$$

Stochastic contractivity (ctd.)

Theorem (Higham, Kloeden, 2005)

Assume (i) – (iii) hold. Then, two solutions $X(t)$ e $Y(t)$ of an Itô SDE with $\mathbb{E}\|X_0\|^2 < \infty$ and $\mathbb{E}\|Y_0\|^2 < \infty$ satisfy

$$\mathbb{E}\|X(t) - Y(t)\|^2 \leq \mathbb{E}\|X_0 - Y_0\|^2 e^{\alpha t},$$

where

$$\alpha = 2\mu + L.$$

$\alpha < 0$ provides **mean-square contractivity**.



D.J. Higham, P.E. Kloeden, *Numerical methods for nonlinear stochastic differential equations with jumps*, Numer. Math. (2005).



E. Buckwar, R. D'Ambrosio, *Exponential mean-square stability properties of stochastic linear multistep methods*, submitted.



R. D'Ambrosio, S. Di Giovacchino *Mean-square contractivity of stochastic θ -methods*, Comm. Nonlinear Sci Numer. Simul. (2021).



R. D'Ambrosio, S. Di Giovacchino *Nonlinear stability issues of stochastic Runge-Kutta methods*, Comm. Nonlinear Sci Numer. Simul. (2021).

Analysis of one-step methods

Theorem

Assume (i) – (iii) hold. Then, any one-step stochastic method

$$\alpha_2 X_{i+1} + \alpha_1 X_i = \Delta t(\beta_2 f(X_{i+1}) + \beta_1 f(X_i) + \gamma_1 g(X_i) \Delta W_i).$$

satisfies the following inequality

$$\mathbb{E}\|X_{i+1} - Y_{i+1}\|^2 \leq \mathbb{E}\|X_0 - Y_0\|^2 e^{\nu t_{i+1}},$$

with

$$\nu = \frac{1}{\Delta t} \log \beta_{\text{OS}},$$

being

$$\beta_{\text{OS}} = \frac{\alpha_1^2 - 2\alpha_1\beta_1\mu\Delta t + \beta_1^2 M\Delta t^2 + \gamma_1^2 L\Delta t^3}{\alpha_2 - 2\beta_2\mu\Delta t}$$

and $M = \sup_{t \in [0, T]} \mathbb{E}|f'(X(t))|^2$.

Contractivity of one-step methods

A one-step method is exponential mean-square contractive if $\nu < 0$, i.e. if

$$0 < \beta_{\text{OS}} < 1.$$

Example: Stochastic trapezoidal rule

$$X_{i+1} = X_i + \frac{1}{2}\Delta t f(X_i) + \frac{1}{2}\Delta t f(X_{i+1}) + g(X_i)\Delta W_i,$$

$$\beta_{\text{OS}} = \frac{4 - 4\mu\Delta t + (M + 4L)\Delta t^2}{4(1 - \mu\Delta t)}.$$

Hence, it is contractive if

$$\Delta t < \frac{8|\mu|}{M + 4L}.$$

Numerical test

Let $f(x) = -4x - x^3$, $g(x) = x$.

Then, $\mu = -4$, $L = 1$.

$\alpha = 2\mu + L = -7 < 0 \Rightarrow$ exponential mean-square contractivity.

Stepsize restriction for the trapezoidal method:

$$\Delta t < \frac{8}{5}.$$

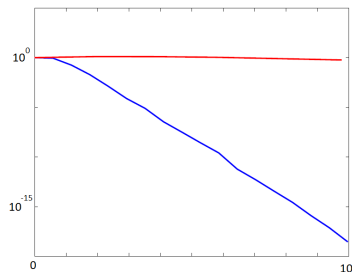


Figure: Mean-square deviations over 1000 paths computed by the trapezoidal method with stepsizes $\Delta t = 75/128 \approx 0.59$ and $\Delta t = 125/64 \approx 1.95$

Useful recursion for two-step methods

Stochastic two-step linear methods (Buckwar *et al.*, BIT 2006)

$$\alpha_2 X_{i+1} + \alpha_1 X_i + \alpha_0 X_{i-1} = \Delta t(\beta_2 f(X_{i+1}) + \beta_1 f(X_i) + \beta_0 f(X_{i-1})) \\ + \gamma_1 g(X_i) \Delta W_i + \gamma_0 g(X_{i-1}) \Delta W_{i-1}.$$

Theorem

Assume (i) – (iii) hold. Then, any two numerical solutions $\{X_i\}_i$ and $\{Y_i\}_i$ generated by a two-step method satisfy

$$\mathbb{E}\|X_{i+1} - Y_{i+1}\|^2 \leq \beta_{\text{TS}} \mathbb{E}\|X_i - Y_i\|^2 + \gamma_{\text{TS}} \mathbb{E}\|X_{i-1} - Y_{i-1}\|^2,$$

with

$$\beta_{\text{TS}} = \frac{\alpha_1^2 + \alpha_0 \alpha_1 + (-2\alpha_1 \beta_1 \mu - (\alpha_1 \beta_0 + \alpha_0 \beta_1 M)) \Delta t + (\beta_1^2 + \beta_1 \beta_0) M \Delta t^2 + \gamma_1^2 L \Delta t^3}{\alpha_2 - 2\beta_2 \mu \Delta t},$$

$$\gamma_{\text{TS}} = \frac{\alpha_0^2 + \alpha_0 \alpha_1 + (-2\alpha_0 \beta_0 \mu - (\alpha_1 \beta_0 M + \alpha_0 \beta_1)) \Delta t + (\beta_0^2 + \beta_1 \beta_0) M \Delta t^2 + \gamma_0^2 L \Delta t^3}{\alpha_2 - 2\beta_2 \mu \Delta t}.$$

Analysis of two-step methods

Theorem

Assume (i) – (iii) hold. Then, any two-step stochastic method satisfies

$$\mathbb{E}\|X_{n+1} - Y_{n+1}\|^2 \leq \mathbb{E}\|X_0 - Y_0\|^2 e^{\eta t_{n+1}},$$

with

$$\eta = \frac{1}{\Delta t} \log(\zeta_{n+1}),$$

where ζ_{n+1} is recursively defined by the three-term formula

$$\zeta_{n+1} = \beta_{\text{TS}}\zeta_n + \gamma_{\text{TS}}\zeta_{n-1},$$

with $\zeta_1 = \beta_{\text{OS}}$ and $\zeta_2 = \beta_{\text{TS}}\beta_{\text{OS}} + \gamma_{\text{TS}}$.

β_{TS} and γ_{TS} are given in the useful recursion; β_{OS} characterizes the one-step method employed to compute the missing starting values X_1 and Y_1 .

Contractivity of two-step methods

A two-step method is exponential mean-square contractive if $\eta < 0$, i.e. if, after performing n steps,

$$0 < \zeta_n < 1,$$

Example: Adams-Moulton method

$$X_{n+1} - X_n = \Delta t \left(\frac{5}{12} f(X_{n+1}) + \frac{8}{12} f(X_n) - \frac{1}{12} f(X_{n-1}) + g(X_n) \Delta W_n \right).$$

It satisfies

$$\beta_{\text{TS}} = \frac{36 - (3 - 48\mu)\Delta t + 14M\Delta t^2 + 36L\Delta t^3}{6(6 - 5\mu\Delta t)},$$
$$\gamma_{\text{TS}} = \frac{(12 + 7\Delta t)M\Delta t}{24(5\mu\Delta t - 6)}.$$

In order to check $0 < \zeta_n < 1$, we compute the values of ζ_n for large enough values of n , assuming to employ the trapezoidal method as a starting method.

Numerical test

Let $f(x) = -4x - x^3$, $g(x) = x$.

Satisfies exponential mean-square contractivity.

Stepsize restriction for the Adams-Moulton method: for $n = 24$, we have

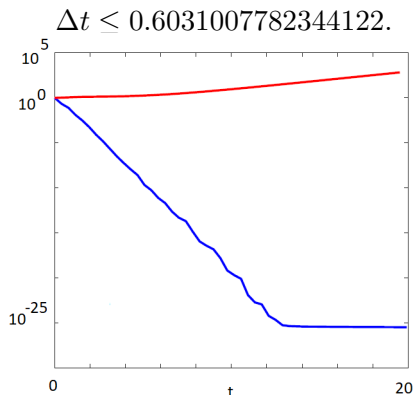


Figure: Mean-square deviations over 1000 paths computed by the Adams-Moulton method with stepsizes $\Delta t = 25/28 \approx 0.89$ and $\Delta t = 75/128 \approx 0.58$

Stochastic θ -methods

θ -Maruyama

$$X_{n+1} = X_n + (1 - \theta)\Delta t f(X_n) + \theta\Delta t f(X_{n+1}) + g(X_n)\Delta W_n,$$

θ -Milstein

$$X_{n+1} = X_n + (1 - \theta)\Delta t f(X_n) + \theta\Delta t f(X_{n+1}) + g(X_n)\Delta W_n \\ + \frac{1}{2}g'(X_n)g(X_n)(\Delta W_n^2 - \Delta t),$$

Nonlinear stability analysis:



R. D'Ambrosio, S. Di Giovacchino *Mean-square contractivity of stochastic θ -methods*, Commun. Nonlinear Sci. Numer. Simul. (2021).

θ -Maruyama

Theorem

Under the assumptions (i)–(iii), any two θ -Maruyama numerical solutions X_n and Y_n , $n \geq 0$, satisfy the inequality

$$\mathbb{E} |X_n - Y_n|^2 \leq \mathbb{E} |X_0 - Y_0|^2 e^{\nu(\theta, \Delta t)t_n},$$

where

$$\nu(\theta, \Delta t) = \frac{1}{\Delta t} \ln \beta(\theta, \Delta t), \quad \beta(\theta, \Delta t) = 1 + \frac{\alpha + (1 - \theta)^2 M \Delta t}{1 - 2\theta\mu\Delta t} \Delta t,$$

with

$$M = \sup_{t \in [0, T]} \mathbb{E} |f'(X(t))|^2.$$

Theorem

For any fixed value of $\theta \in [0, 1]$, $|\nu(\theta, \Delta t) - \alpha| = \mathcal{O}(\Delta t)$.

θ -Milstein

Theorem

Under the assumptions (i)–(iii), any two θ -Maruyama numerical solutions X_n and Y_n , $n \geq 0$, satisfy the inequality

$$\mathbb{E} |X_n - Y_n|^2 \leq \mathbb{E} |X_0 - Y_0|^2 e^{\epsilon(\theta, \Delta t)t_n},$$

where

$$\epsilon(\theta, \Delta t) = \frac{1}{\Delta t} \ln \gamma(\theta, \Delta t), \quad \gamma(\theta, \Delta t) = \beta(\theta, \Delta t) + \frac{\widetilde{M} \Delta t^2}{2(1 - 2\theta\mu\Delta t)},$$

with $\widetilde{M} = \sup_{t \in [0, T]} \mathbb{E} |h'(X(t))|^2$, $h(X(t)) = g(X(t))g'(X(t))$.

Theorem

For any fixed value of $\theta \in [0, 1]$, $|\epsilon(\theta, \Delta t) - \alpha| = \mathcal{O}(\Delta t)$.

Region of mean-square contractivity

Definition

For a nonlinear stochastic differential equation satisfying assumptions (i) – (iii), a θ -method is said to generate mean-square contractive numerical solutions in a region $\mathcal{R} \subseteq \mathbb{R}^+$ if, for a fixed $\theta \in [0, 1]$,

$$\nu(\theta, \Delta t) < 0, \quad \forall \Delta t \in \mathcal{R}$$

for the θ -Maruyama,

$$\epsilon(\theta, \Delta t) < 0, \quad \forall \Delta t \in \mathcal{R}$$

for the θ -Milstein.

Definition

A stochastic θ -method is said unconditionally mean-square contractive if, for a given $\theta \in [0, 1]$, $\mathcal{R} = \mathbb{R}^+$.

Mean-square contractivity: θ -Maruyama

Mean-square contractivity holds true if

$$0 < \beta(\theta, \Delta t) < 1,$$

for any $\Delta t \in \mathcal{R}$, i.e.

$$\mathcal{R} = \begin{cases} \left(0, \frac{|\alpha|}{(1-\theta)^2 M}\right), & \theta < 1, \\ \mathbb{R}^+, & \theta = 1. \end{cases}$$

The θ -Maruyama method with $\theta = 1$ (implicit Euler-Maruyama) is unconditionally mean-square contractive.

Mean-square contractivity: θ -Milstein

Mean-square contractivity holds true if

$$0 < \gamma(\theta, \Delta t) < 1,$$

for any $\Delta t \in \mathcal{R}$, i.e.

$$\mathcal{R} = \begin{cases} \left(0, \frac{2|\alpha|}{2(1-\theta)^2 M + \widetilde{M}} \right), & \theta < 1, \\ \left(0, \frac{2|\alpha|}{\widetilde{M}} \right), & \theta = 1. \end{cases}$$

Parameter estimation as in global optimization algorithms.

Numerical experiments

Problem 1: stochastic Ginzburg-Landau

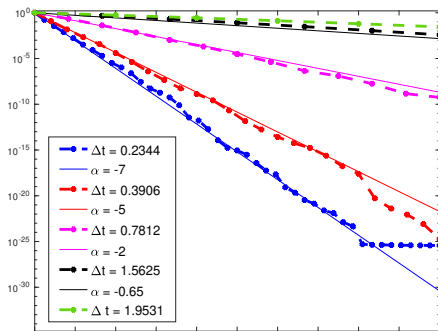


M. Hutzenthaler, A. Jentzen, Numerical approximations of stochastic differential equations with non- globally Lipschitz continuous coefficients, *Memoirs of the American Mathematical Society* 236(1112), doi: 10.1090/memo/1112 (2015).

$$f(X(t)) = -4X(t) - X(t)^3, \quad g(X(t)) = X(t)$$

$X_0 = 1, Y_0 = 0$. For this problem $L = 1$ and $\mu = -4$, so $\alpha = -7 < 0$.

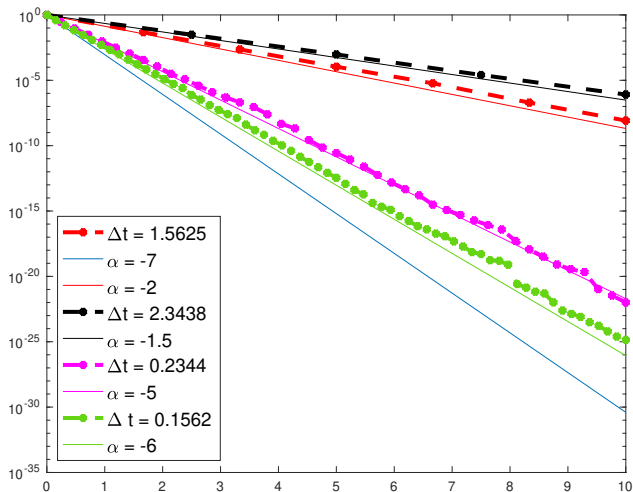
- stochastic trapezoidal methods ($\theta = 1/2$): $\mathcal{R} = (0, \frac{7}{4})$;



Numerical experiments

Problem 1 (ctd.)

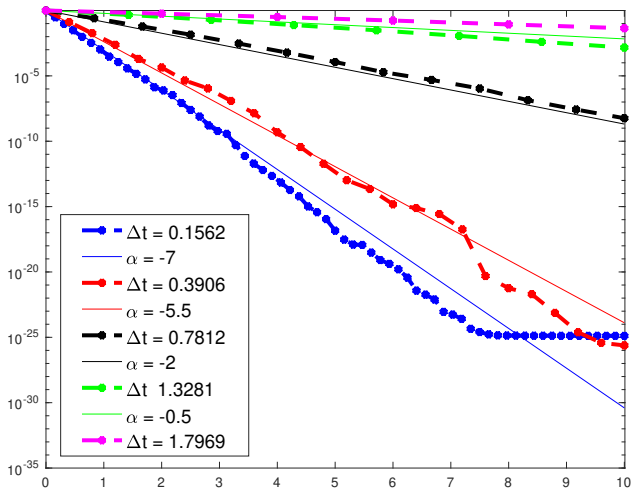
- stochastic implicit Euler, unconditionally mean-square contractive;



Numerical experiments

Problem 1 (ctd.)

- θ -Milstein method with $\theta = 1/2$: $\mathcal{R} = (0, \frac{14}{9})$.



Numerical experiments

Problem 2

$$f(X(t)) = -4 \begin{bmatrix} \sin(X_1(t)) \\ \sin(X_2(t)) \end{bmatrix}, \quad g(X(t)) = \frac{1}{7} \begin{bmatrix} X_1(t) & \frac{3}{2}X_2(t) \\ \frac{5}{2}X_1(t) & -\frac{1}{2}X_2(t) \end{bmatrix}.$$

Initial data: $X_0 = [1 \ 1]^\top$ and $Y_0 = [0 \ 0]^\top$. For this problem the constants L and μ are estimated as $L = 0.148$ and $\mu = -3.56$, so $\alpha \approx -7.5 < 0$.

- Stochastic trapezoidal method: $\mathcal{R} = (0, 1.1875)$;
- stochastic implicit Euler method, unconditionally mean-square contractive.

Numerical experiments

Problem 2 (ctd.)

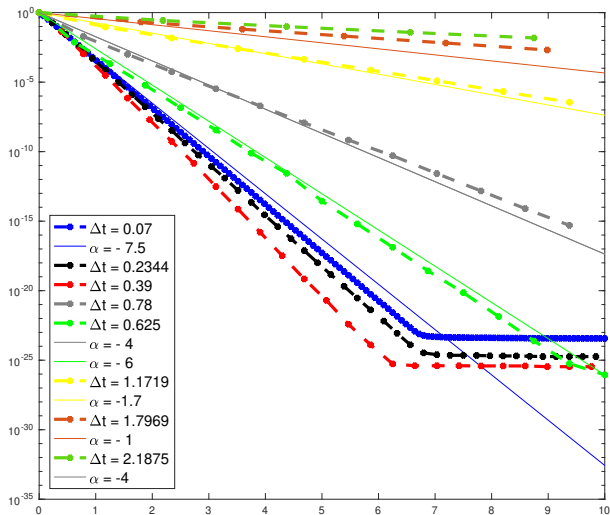


Figure: Mean-square deviations over 2000 paths for the trapezoidal method.

Numerical experiments

Problem 2 (ctd.)

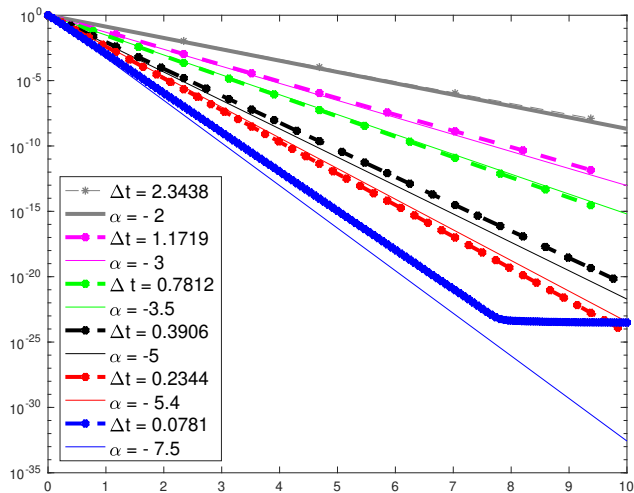


Figure: Mean-square deviations over 2000 paths for the implicit Euler method.