

Principles of stochastic geometric numerical integration

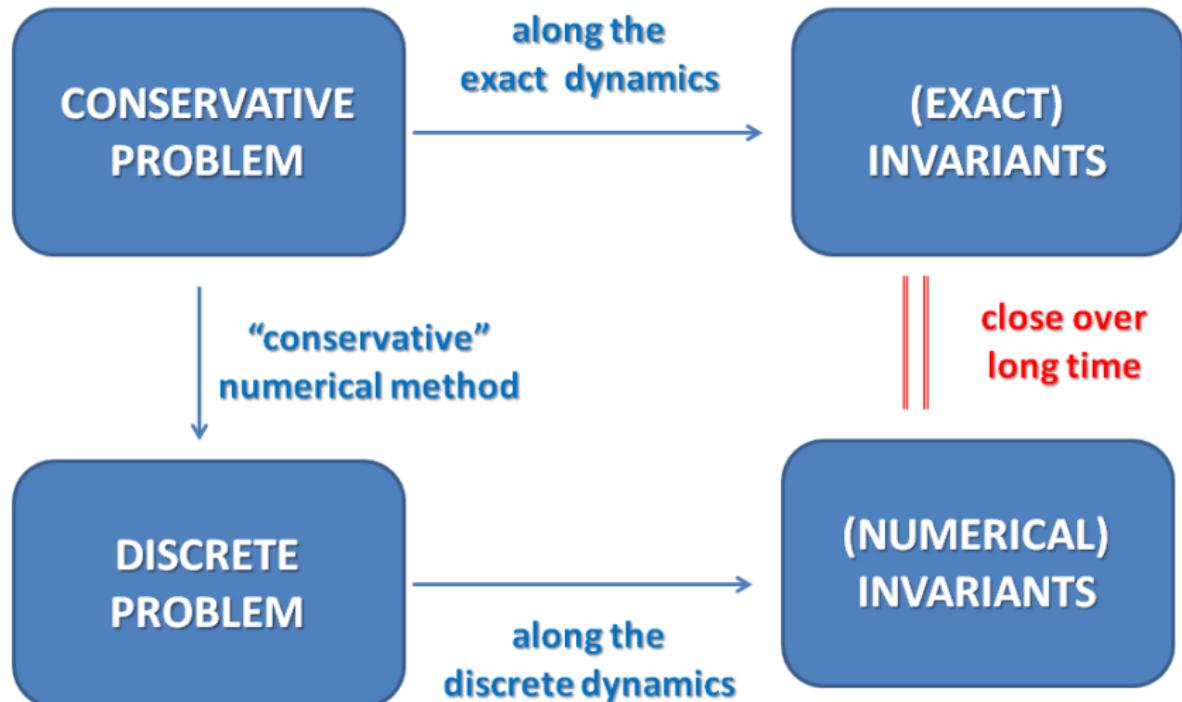
Part II: stochastic Hamiltonian problems

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The numerics of preserving structures



Deterministic Hamiltonians: *memorandum*

$$\begin{aligned}\dot{y}(t) &= J \nabla \mathcal{H}(y(t)), \quad t \geq 0, \\ y(0) &= y_0,\end{aligned}$$

$$J = \begin{bmatrix} 0 & -I \\ I & 0 \end{bmatrix}.$$

- $y(t) = \begin{bmatrix} p(t) \\ q(t) \end{bmatrix} \in \mathbb{R}^{2d}$, generalized **moments** and **coordinates**;
- the Hamiltonian function

$$\mathcal{H} : \mathbb{R}^{2d} \rightarrow \mathbb{R}$$

is a first integral of the problem:

$$\mathcal{H}(y(t)) = \mathcal{H}(y_0), \quad t \geq 0.$$

Indeed,

$$\frac{d}{dt} \mathcal{H}(y(t)) = \nabla \mathcal{H}(y(t))^T \dot{y}(t) = \nabla \mathcal{H}(y(t))^T J^{-1} \nabla \mathcal{H}(y(t)) = 0.$$

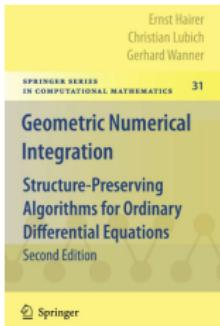
Conservative integrators

- **Symplectic Runge-Kutta** methods exactly preserve quadratic Hamiltonians;
- if the solution, computed by a Runge-Kutta method of order p , lays in a **compact set**, then

$$\mathcal{H}(y_n) = \mathcal{H}(y_0) + \mathcal{O}(h^p),$$

over exponentially long times
(Benettin-Giorgilli, 1994);

- nearly preserving **linear multistep methods**
over long times (Hairer-Lubich, 2004);
- nearly preserving **multivalue methods** (Butcher, D'Ambrosio, 2017; D'Ambrosio, Hairer, 2013, 2014).



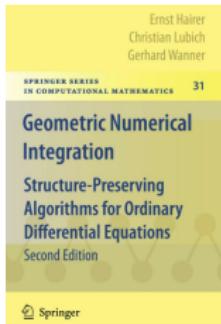
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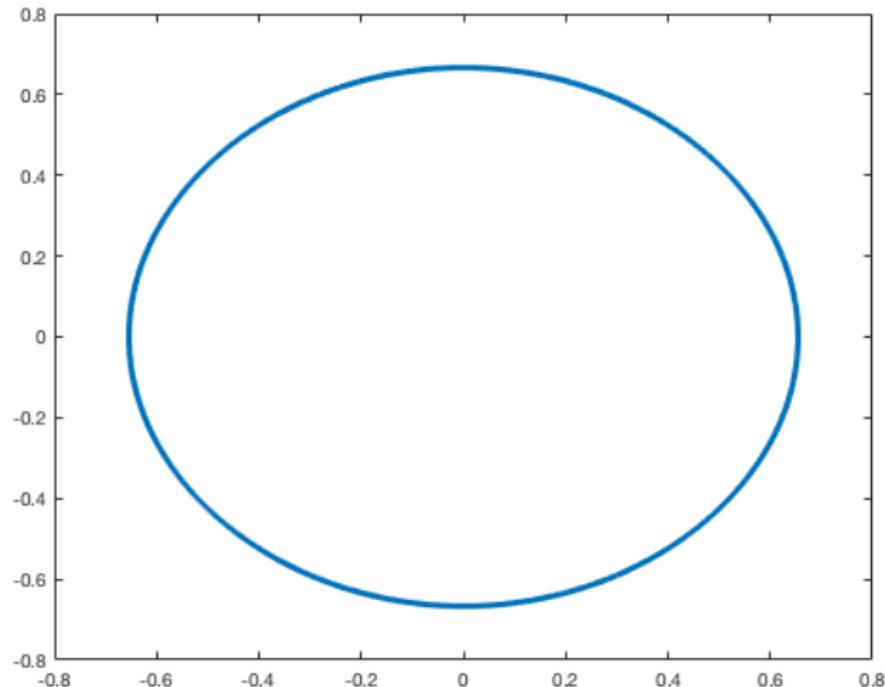
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Example: pendulum

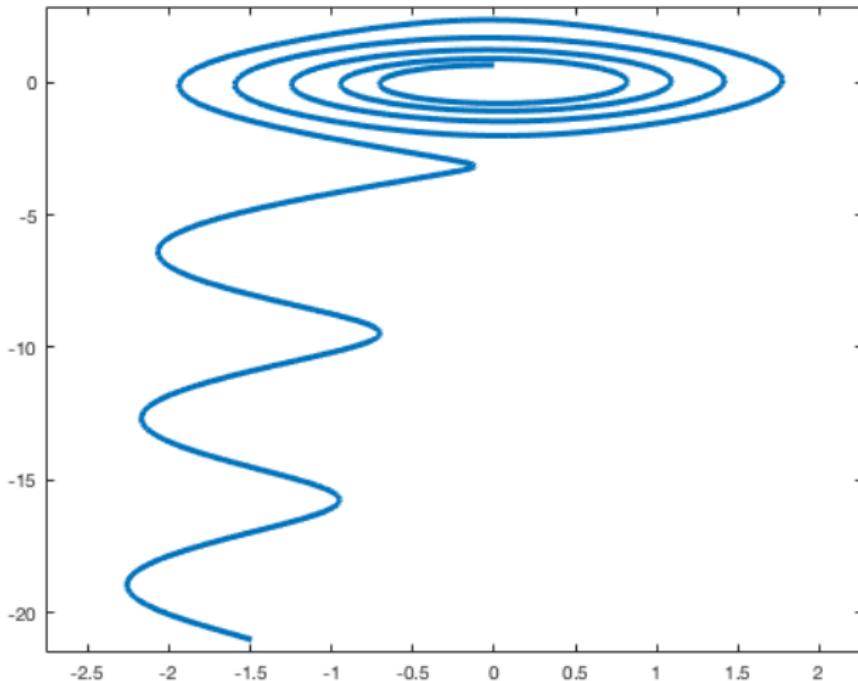
$$\mathcal{H}(y) = \frac{p^2}{2} - \cos q.$$

Simple pendulum



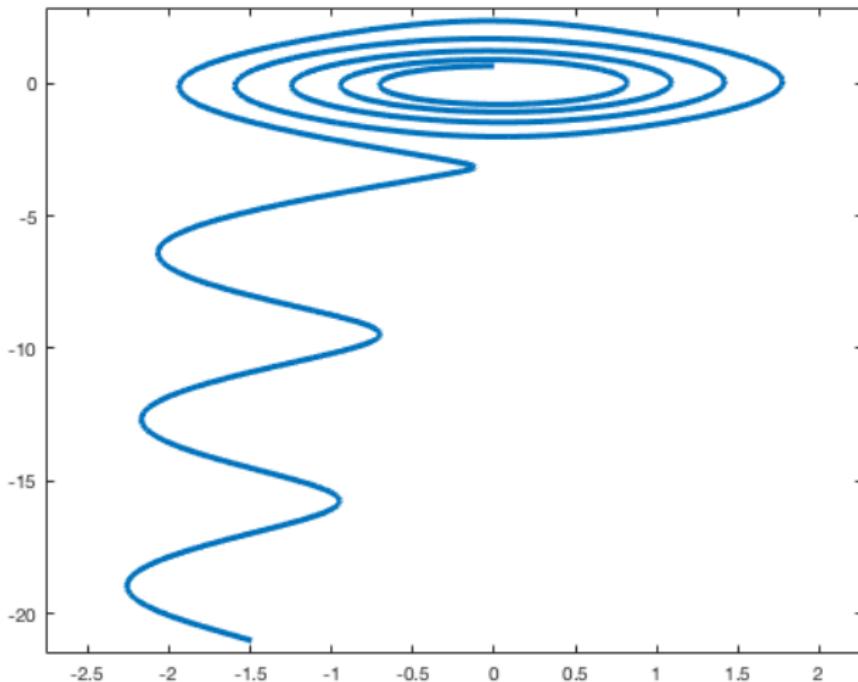
2-stage Gaussian Runge-Kutta method (symplectic)

Simple pendulum (ctd.)



Explicit Euler method (non-symplectic)

Simple pendulum (ctd.)



Explicit Euler method (non-symplectic)



Uri M. Ascher, Surprising computations, Appl. Numer. Math. (2012).

Stochastic differential equations

Itō problem:

$$dX(t) = f(X(t))dt + g(X(t))dW(t), \quad t \geq 0,$$

$$f : \mathbb{R}^d \rightarrow \mathbb{R}^d \text{ (drift)}, \quad g : \mathbb{R}^d \rightarrow \mathbb{R}^{d \times m} \text{ (diffusion)},$$

$W(t)$ m -dimensional Wiener process.

Integral form:

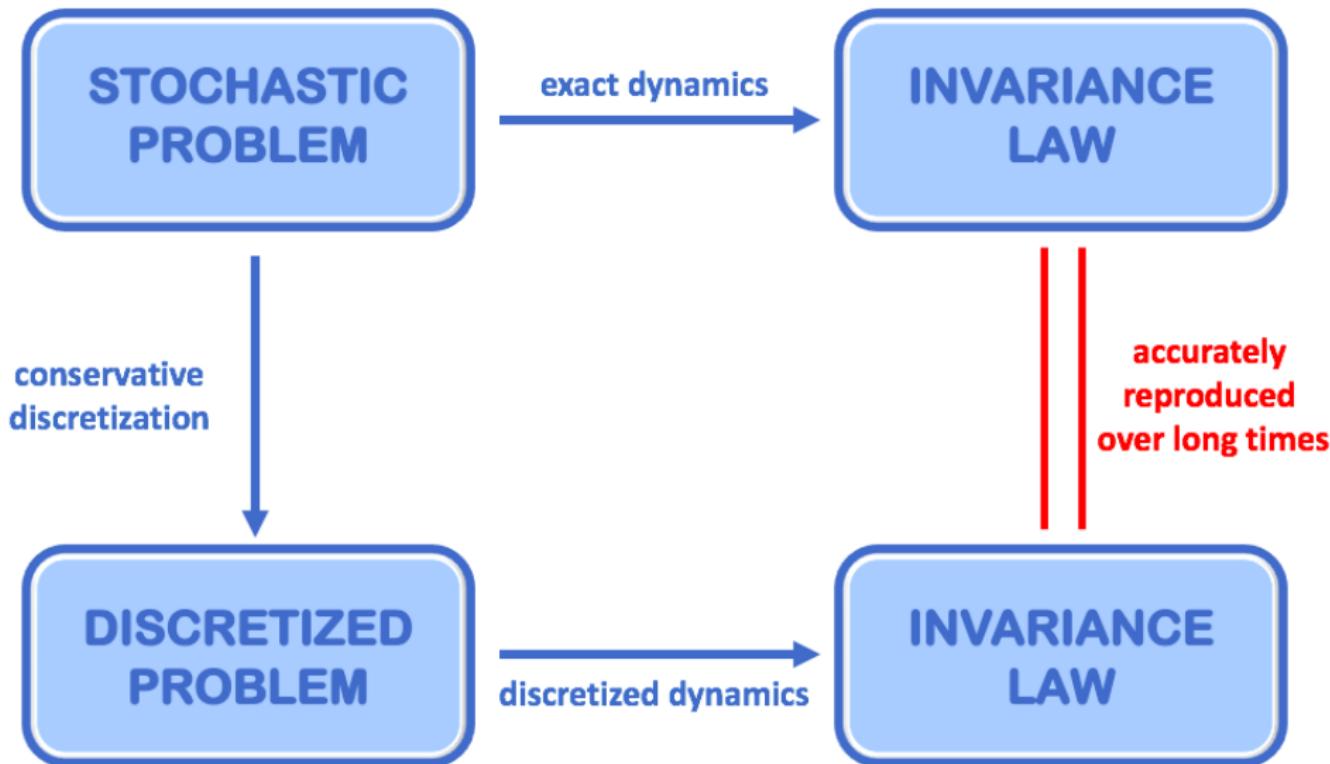
$$X(t) = X(0) + \int_0^t f(X(s))ds + \underbrace{\int_0^t g(X(s))dW(s)}_{\text{Itō integral*}}.$$

*On a uniform grid $\{0 < t_1 < t_2 < \dots \leq t_n\}$, it is defined as

$$\lim_{n \rightarrow \infty} \sum_{j=1}^n g(X(t_j))(W(t_{j+1}) - W(t_j)).$$

Wiener increments are $\sqrt{h} \cdot \mathcal{N}(0, 1)$ – distributed, where $h = t_{j+1} - t_j$.

Stochastic geometric numerical integration



Stochastic geometric numerical integration

- Invariance of asymptotic laws in the discretization of **linear systems** (Schurz, 1999);
- long-term conservation of stationary densities for **stochastic linear oscillators** (Melbo, Higham, 2004; Burrage, Lythe, 2007, 2009; Welfert, 2017; D'Ambrosio, Moccaldi, Paternoster, 2018) and **nonlinear oscillators** (D'Ambrosio, Scalzone, 2020);
- stochastic **Runge-Kutta** per separable Hamiltonians (Burrage 2012, 2014).
- energy-preserving methods for **stochastic Hamiltonian problems**.



C. Chen, D. Cohen, R. D'Ambrosio, A. Lang, *Drift-preserving numerical integrators for stochastic Hamiltonian systems*, Adv. Comput. Math. 46, article number 27 (2020).



R. D'Ambrosio, G. Giordano, B. Paternoster, A. Ventola, *Perturbative analysis of stochastic Hamiltonian problems under time discretizations*, Appl. Math. Lett. 120, article number 107223 (2021).

Stochastic Hamiltonian problems

For Hamiltonians of the form

$$\mathcal{H}(p(t), q(t)) = \frac{1}{2} p^\top p + V(q), \quad t \geq 0,$$

with $V: \mathbb{R}^d \rightarrow \mathbb{R}$ sufficiently smooth potential, we consider

$$\begin{aligned} dq(t) &= p(t) dt \\ dp(t) &= -V'(q(t)) dt + \Sigma dW(t). \end{aligned}$$

with $\Sigma \in \mathbb{R}^{d \times m}$.

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Invariance trace law (Burrage, 2014)

$$\mathbb{E} [\mathcal{H}(p(t), q(t))] = \mathbb{E} [\mathcal{H}(p(t_0), q(t_0))] + \frac{1}{2} \text{Tr} (\Sigma^\top \Sigma) t$$

Linear drift in the expected Hamiltonian.

Stochastic Hamiltonian problems

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Linear drift in the expected Hamiltonian.

Is this property naturally preserved along discretizations?

Augmented stochastic Runge-Kutta methods

Consider a general scalar ($d = 1$) additive noise problem

$$dy = f(y) dt + \varepsilon r dW,$$

$y, r \in \mathbb{R}^2$, $\varepsilon \in \mathbb{R}$, $W(t)$ a scalar Wiener process.

- Burrage (2012): **a single Wiener increment** per step does not permit the preservation of the stochastic Hamiltonian structure;
- Burrage (2014): consider **$s+1$ independent samples** per step

$$\begin{aligned} Y_i &= y_n + h \sum_{j=1}^s a_{ij} f(Y_j) + \varepsilon \sum_{j=1}^i z_j r, \\ y_{n+1} &= y_n + h \sum_{j=1}^s b_j f(Y_j) + \varepsilon \sum_{j=1}^{s+1} z_j r, \end{aligned}$$

$$\begin{aligned} z_i &= W(t_n + hc_i) - W(t_n + hc_{i-1}) = \sqrt{c_i - c_{i-1}} \Delta W_i, \quad i = 1, \dots, s+1, \\ c_0 &= 0, \quad c_{s+1} = 1. \end{aligned}$$

Example: augmented midpoint rule

The augmented midpoint rule (Burrage, 2012)

$$Y = y_n + \frac{h}{2} f(Y) + \frac{\sqrt{2}}{2} \Delta W_1 \varepsilon r,$$
$$y_{n+1} = y_n + h f(Y) + \frac{\sqrt{2}}{2} (\Delta W_1 + \Delta W_2) \varepsilon r.$$

applied to the linear problem

$$dy = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} y dt + \varepsilon r dW,$$

exactly preserves the expected value of the Hamiltonian $\mathcal{H}(p, q) = \frac{1}{2}(p^2 + q^2)$, given by

$$\mathbb{E}[\mathcal{H}(p(t), q(t))] = \mathbb{E}[\mathcal{H}(p(t_0), q(t_0))] + \frac{\varepsilon^2}{2}(t - t_0).$$

Hence, after one single step, denoting by $\mathcal{H}_n \approx \mathcal{H}(p(t_n), q(t_n))$,

$$\mathbb{E}[\mathcal{H}_n] = \mathbb{E}[\mathcal{H}_{n-1}] + \frac{\varepsilon^2}{2}h.$$

Nonlinear case

Double well potential with Hamiltonian

$$\mathcal{H}(p, q) = \frac{1}{2}p^2 + \frac{1}{4}q^4 - \frac{1}{2}q^2, \quad t \in [0, 40].$$

- MQ: $y_{n+1} = y_n + \frac{h}{6} \left(f(y_n) + 4f\left(\frac{y_n+y_{n+1}}{2}\right) + f(y_{n+1}) \right)$. Preserves deterministic quartic Hamiltonians (Celledoni, 2013); energy-preserving B-series method (Chartier, 2006);
- L: Lobatto IIIA (symmetric, non-symplectic);
- IM: augmented implicit midpoint rule

Table 1 Errors in $E(H(40))$ for the three methods

ϵ	h	MQ	L	IM
0	0.05	9.5(-15)	7.9(-7)	4.3(-4)
0	0.2	5.6(-14)	2.1(-4)	6.1(-3)
0.001	0.1	8.4(-6)	2.1(-5)	1.6(-3)
0.01	0.1	1.5(-5)	4.7(-6)	1.2(-4)
0.01	0.2	4.3(-5)	1.5(-4)	6.0(-3)
0.5	0.05	1.5(-2)	8.0(-3)	1.2(-2)
0.5	0.2	1.6(-2)	6.5(-3)	6.9(-2)

ε -expansions

- Classical idea in the deterministic setting (e.g. singularly perturbed problems; see Hairer, Wanner monographs).
- A toy example:

$$x^2 + 2\varepsilon x - 1 = 0, \quad \varepsilon \ll 1.$$

Ansatz: $x = \sum_{n=0}^{\infty} x_n \varepsilon^n$. Replacing the ansatz in the equation and collecting the powers of ε we get

$$\varepsilon^0 : \quad x_0^2 - 1 = 0$$

$$\varepsilon^1 : \quad 2x_0(x_1 + 1) = 0$$

$$\varepsilon^2 : \quad x_1^2 + 2x_0x_2 + 2x_1 = 0$$

$$x \approx x_\varepsilon = \pm 1 - \varepsilon \pm \frac{\varepsilon^2}{2}$$

	$\varepsilon = 10^{-1}$	$\varepsilon = 10^{-3}$
$ x^+ - x_\varepsilon^+ $	1.24e-5	1.25e-13

ε -expansions

Consider the linear scalar test problem

$$\begin{bmatrix} dq \\ dp \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} y \, dt + \begin{bmatrix} \sigma \\ 0 \end{bmatrix} \, dW,$$

corresponding to the second order problem

$$\ddot{q} = -q + \sigma \xi(t),$$

where $\xi(t)$ is a Gaussian white noise. Generally, the literature considers as test problem

$$\boxed{\ddot{q} = -q + \varepsilon \sqrt{t}}$$

with $\varepsilon \sim \mathcal{N}(0, \sigma^2)$. **Ansatz:**

$$\boxed{q(t) = q_0(t) + \varepsilon q_1(t) + \varepsilon^2 q_2(t) + \dots}$$

ε -expansions (ctd.)

Replace the ansatz in the equation and collect in powers of ε , leads to

$$\begin{aligned}\varepsilon^0 : \quad & \ddot{q}_0 + q_0 = 0 \\ \varepsilon^1 : \quad & \ddot{q}_1 + q_1 = \sqrt{t} \\ & \vdots\end{aligned}$$

We have

$$\boxed{\begin{aligned}q(t) &= \cos(t) + \sin(t) - \varepsilon \left(\sqrt{\frac{\pi}{2}} C \left(\sqrt{\frac{2}{\pi}} \sqrt{t} \right) \cos(t) + \sqrt{\frac{\pi}{2}} S \left(\sqrt{\frac{2}{\pi}} \sqrt{t} \right) \sin(t) + \sqrt{t} \right) + \dots \\ p(t) &= \cos(t) - \sin(t) + \varepsilon \sqrt{\frac{\pi}{2}} \left(C \left(\sqrt{\frac{2}{\pi}} \sqrt{t} \right) \sin(t) - S \left(\sqrt{\frac{2}{\pi}} \sqrt{t} \right) \cos(t) \right) + \dots\end{aligned}}$$

where S e C are the Fresnel integrals

$$S(x) = \int_0^x \sin \left(\frac{\pi}{2} t^2 \right) dt,$$

$$C(x) = \int_0^x \cos \left(\frac{\pi}{2} t^2 \right) dt.$$

ε -expansions (ctd.)

$$q(t) = \cos(t) + \sin(t) - \varepsilon \left(\sqrt{\frac{\pi}{2}} C \left(\sqrt{\frac{2}{\pi}} \sqrt{t} \right) \cos(t) + \sqrt{\frac{\pi}{2}} S \left(\sqrt{\frac{2}{\pi}} \sqrt{t} \right) \sin(t) + \textcolor{red}{\sqrt{t}} \right) + \dots$$
$$p(t) = \cos(t) - \sin(t) + \varepsilon \sqrt{\frac{\pi}{2}} \left(C \left(\sqrt{\frac{2}{\pi}} \sqrt{t} \right) \sin(t) - S \left(\sqrt{\frac{2}{\pi}} \sqrt{t} \right) \cos(t) \right) + \dots$$

- $\textcolor{red}{\sqrt{t}}$: secular term;
- in the long-term integration, the secular term becomes dominant;
- in the long-term integration, the modified Hamiltonian (arising from the ε -solution) significantly differs from the original one;
- energy-drift preservation is not a characteristic property of stochastic methods.



R. D'Ambrosio, G. Giordano, B. Paternoster, A. Ventola, *Perturbative analysis of stochastic Hamiltonian problems under time discretizations*, Appl. Math. Lett. 120, article number 107223 (2021).

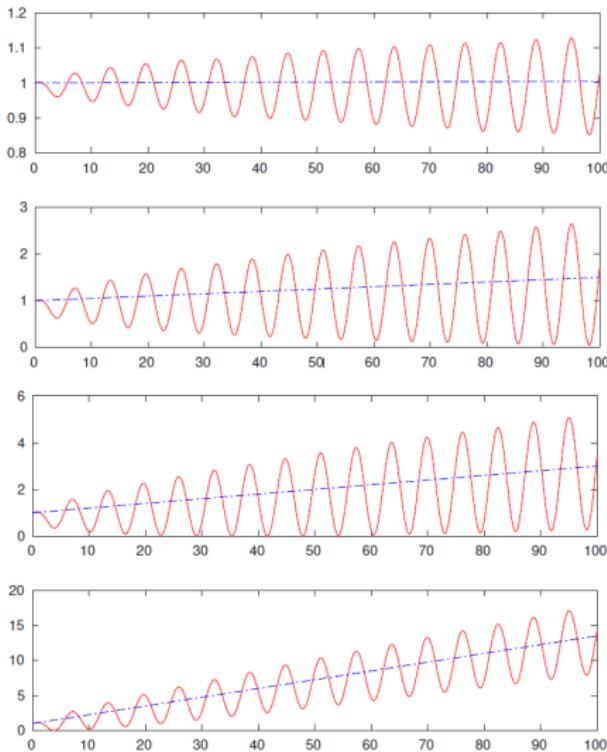


Figure: Comparison between the expectation of the modified Hamiltonian (red) and the original Hamiltonian (blue) for $\varepsilon = 0.01; 0.1; 0.2; 0.5$.

Numerical preservation of the trace law (ctd.)



C. Chen, D. Cohen, R. D'Ambrosio, A. Lang, Drift-preserving numerical integrators for stochastic Hamiltonian systems, Adv. Comp. Math. (2020).

$$\begin{aligned}\Psi_{n+1} &= p_n + \Sigma \Delta W_n - \frac{h}{2} \int_0^1 V'(q_n + sh\Psi_{n+1}) ds, \\ q_{n+1} &= q_n + h\Psi_{n+1},\end{aligned}\tag{\star}$$

$$p_{n+1} = p_n + \Sigma \Delta W_n - h \int_0^1 V'(q_n + sh\Psi_{n+1}) ds.$$

Theorem

If $V \in \mathcal{C}^1(\mathbb{R}^d)$, the scheme (\star) satisfies the trace law

$$\mathbb{E} [\mathcal{H}(p_n, q_n)] = \mathbb{E} [\mathcal{H}(p(t_0), q(t_0))] + \frac{1}{2} \text{Tr} (\Sigma^\top \Sigma) t_n,$$

for any grid point $t_n = nh$.

Numerical preservation of the trace law (ctd.)

Theorem

If V' is Lipschitz continuous, then there exists $h^* > 0$ such that, for any $0 < h \leq h^*$, the scheme (\star) converges with order 1 in the mean-square sense, i.e.,

$$(\mathbb{E} [|q(t_n) - q_n|^2])^{1/2} + (\mathbb{E} [|p(t_n) - p_n|^2])^{1/2} \leq Ch,$$

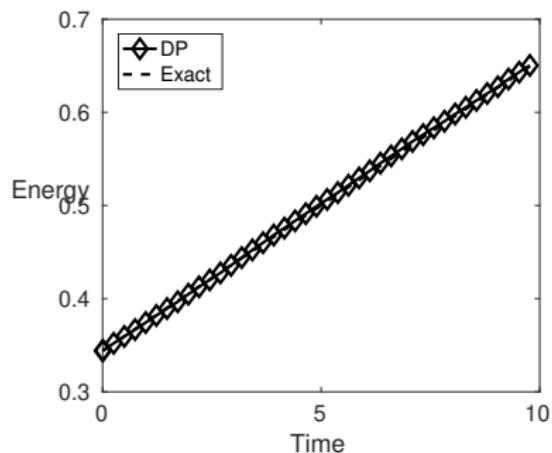
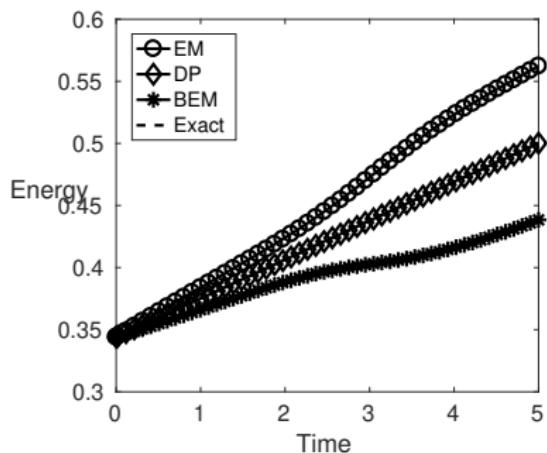
where the constant C is independent on h and n .

Other properties

- Error analysis in the strong and weak senses;
- error analysis in dependence on the estimation of the expected value (Monte Carlo, Monte Carlo multilevel, ...);
- long-term analysis of the Hamiltonian error.

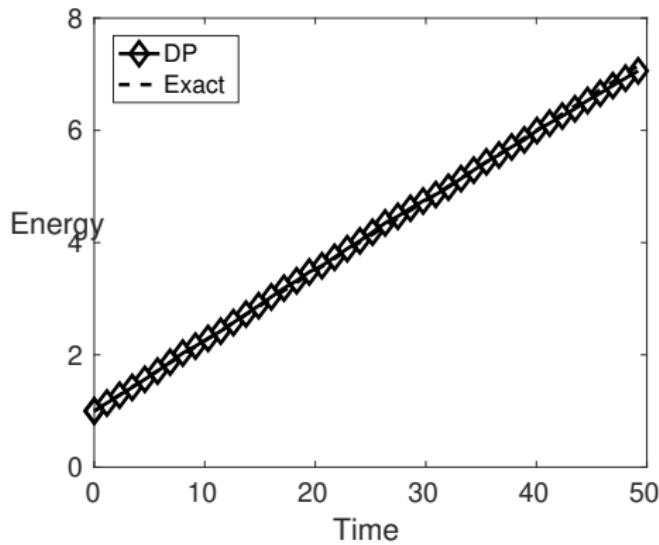
Numerical test (stochastic pendulum)

$$H(p, q) = \frac{1}{2}p^2 - \cos(q), \quad \sigma = 0.25, \quad (p_0, q_0) = (1, \sqrt{2}).$$



Numerical test (double-well potential)

$$H(p, q) = \frac{1}{2}p^2 + \frac{1}{4}q^4 - \frac{1}{2}q^2, \quad \sigma = 0.5, \quad (p_0, q_0) = (\sqrt{2}, \sqrt{2}).$$



Numerical test (Hénon-Heiles with double noise)

$$H(p, q) = \frac{1}{2} (p_1^2 + p_2^2) + \frac{1}{2} (q_1^2 + q_2^2) + \alpha \left(q_1 q_2 - \frac{1}{3} q_1^3 \right),$$

$$\Sigma = \begin{pmatrix} 0.2 & 0 \\ 0 & 0.2 \end{pmatrix}, \quad p_0 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \quad q_0 = \begin{pmatrix} \sqrt{3} \\ 1 \end{pmatrix}, \quad \alpha = 1/16.$$

