On the time-scale of B-series methods and symplectic integration

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Beijing, May 2009

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Hamiltonian systems

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Example

Perturbed Kepler problem: We consider (for $0 < \epsilon << 1$)

$$H(p,q) = \frac{1}{2} ||p||^2 + V(||q||), \text{ where } V(r) = -\frac{1}{r} - \frac{\epsilon}{3r^3}.$$

Implicit midpoint: The approximations $y_n \approx y(t_n)$ for $t_n = nh$, are implicitly defined as

$$y_n = y_{n-1} + h f(\frac{1}{2}(y_{n-1} + y_n)), \quad f(y) = J^{-1} \nabla H(y).$$

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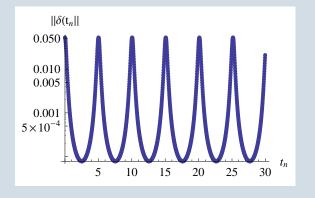
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Example (Application to implicit midpoint to perturbed Kepler)

$$y(0) = (1 - e, 0, 0, \sqrt{\frac{1+e}{1-e}}), e = 0.6, \epsilon = 0.015, h = 0.02$$

Local error $\delta(t_n)$ (in logarithmic scale) versus time t_n :



 $\max_{n} ||\delta(t_{n})|| = 0.052762, \quad \max_{n} ||y_{n} - y(t_{n})|| = 0.92829.$

Time transformation

Consider a ficticious time variable au such that $t = t(\tau)$ is defined as the solution of

$$\frac{d}{d\tau}t = s(y(t)), \quad t(0) = 0$$

for a suitably chosen function s(y), and obtain $x(\tau) = y(t(\tau))$ by integrating

$$\frac{d}{d\tau}t = s(x), \quad \frac{d}{d\tau}x = s(y)f(x),$$

with x(0) = y(0) and t(0) = 0.

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- The new ODE system is not Hamiltonian.

Adaptative symplectic integration (Hairer 1997, Reich 1999)

Consider a new Hamiltonian function

$$\mathcal{H}(y) = s(y)(H(y) - H_0), \quad H_0 = H(y(0)),$$

so that $t = t(\tau)$, $x(\tau) = y(t(\tau))$ is the solution of

$$rac{d}{d au}t=s(x),\quad rac{d}{d au}x=J^{-1}
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with x(0) = y(0) and t(0) = 0.

We normalize s, when integrating for $t \in [0, t_f]$ in such a way that,

$$\int_0^{t_f} s(y(t(\tau))) \, d\tau = t_f.$$

Ideally: Find s(y) such that, once normalized, minimize the discretization errors in some sense.

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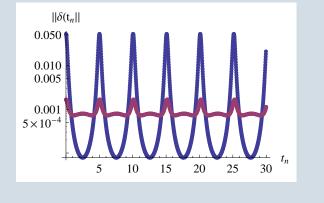
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Example (Adaptative symplectic integration of perturbed Kepler)

We consider $s(p,q) = c ||q||^{3/2}$ (Budd and Piggott 2003). Local error $\delta(t_n)$ (in logarithmic scale) versus time t_n :



 $\max_{n} ||\delta(t_{n})|| = 0.00166186, \quad \max_{n} ||y_{n} - y(t_{n})|| = 0.00429137.$

Backward error analysis for B-series methods

Modified equations of a one-step method of order N

 $y_n = \bar{y}(t_n)$, where $\bar{y}(t)$ is the solution of a nearby problem

$$\frac{d}{dt}\bar{y} = f(\bar{y}) + h^N f_N(\bar{y}) + h^{N+1} f_{N+1}(\bar{y}) + \cdots, \quad \bar{y}(0) = y_0.$$

For a B-series method (RK, \cdots

$$f_{j-1}(y) = \sum_{u \in \mathcal{T}_j} \frac{b(u)}{\sigma(u)} F(u)(y),$$

where \mathcal{T}_j is the set of rooted trees with j vertices, and $\forall u \in \mathcal{T}_j$,

- $b(u) \in \mathbb{R}$ depends on the method,
- F(u)(y) is the elementary differential of u associated with f,
- $\sigma(u) \in \mathbb{Z}^+$ is a normalization factor

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Rigorous backward error analysis for B-series methods

Rigorous backward error analysis: Benettin and Giorgilli (1994), Hairer and Lubich (1997), Reich (1999).

Estimates for real analytic ODE systems

There exists $\lambda : \cup \mathcal{T}_j \to \mathbb{R}$ such that, given a norm $|| \cdot ||$ on \mathbb{R}^D and f(y) real analytic, $\exists L(y), C(y) > 0$ such that $\forall u \in \mathcal{T}_j$,

$$\frac{1}{\sigma(u)} ||F(u)(y)|| \leq \lambda(u) C(y) L(y)^{j-1},$$

$$||h^{j} f_{j}(y)|| \leq d_{j} C(y) (hL(y))^{j-1},$$

, where $d_j = \sum_{u \in \mathcal{T}_j} \lambda(u) |b(u)|.$

If these estimates are tight enough, then $hL(y_n)$ somehow reflects the *time-scale* of $y_n = \bar{y}(t_n)$ at $t = t_n$. Aim: Find a normalized s(y) that minimizes max $L(y_n)$.

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If these estimates are tight enough, then $hL(y_n)$ somehow reflects the *time-scale* of $y_n = \overline{y}(t_n)$ at $t = t_n$. Aim: Find a normalized s(y) that minimizes max $L(y_n)$. How to obtain L(y)? Let $|| \cdot ||$ be a norm in \mathbb{C}^D .

Preliminary estimates for real analytic f(y)

$$\tilde{L}(y) = \max_{||z-y|| \leq 1} ||f(z)||,$$

where f(z) is the complex analytic extension of f(y). Then,

$$\frac{1}{\sigma(u)} ||F(u)(y)|| \leq \lambda(u) \, \tilde{L}(y)^{j}.$$

Observation: For invertible matrices $\mathcal{P} \in \mathbb{R}^{D \times D}$,

$$\begin{array}{ccc} f(y) & \longrightarrow & \hat{f}(\hat{y}) & = \mathcal{P}f(\mathcal{P}^{-1}\hat{y}) \\ \downarrow & & \downarrow \\ F(u)(y) & \longrightarrow & \hat{F}(u)(\hat{y}) & = \mathcal{P}F(u)(\mathcal{P}^{-1}\hat{y}) \end{array}$$

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This implies that

$$\frac{1}{\sigma(u)} ||F(u)(y)|| \leq \lambda(u) C_{\mathcal{P}}(y) L_{\mathcal{P}}(y)^{j-1},$$

where

$$L_{\mathcal{P}}(y) = \max_{||\mathcal{P}(z-y)|| \le 1} ||\mathcal{P} f(z)||, \quad C_{\mathcal{P}}(y) = ||\mathcal{P}^{-1}|| L_{\mathcal{P}}(y).$$

Time-scale function L(y)

$$L(y) = \inf_{\mathcal{P}} \max_{||\mathcal{P}(z-y)|| \leq 1} ||\mathcal{P}f(z)||.$$

If $\exists \mathcal{P} = \mathcal{P}(y)$ such that $L_{\mathcal{P}}(y) = L(y)$, then our estimates for the elementary differentials ||F(u)(y)|| hold with L(y) and

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Example (Perturbed Kepler problem)

If H(p,q) < 0, then there exist $\mu, \nu, c_1, c_2 > 0$ such that

$$L_{\mathcal{P}}(p,q) \; \leq \; ilde{L}_{\mathcal{P}}(p,q) := c_1 \, ||q||^{-3/2} + \epsilon \, c_2 \, ||q||^{-7/2}$$

for

$$\mathcal{P} = \left(\begin{array}{cc} \frac{\mu}{\sqrt{||q||}} I_2 & 0\\ 0 & \nu ||q|| I_2 \end{array}\right)$$

It then seems reasonable to choose $s(p,q) \approx L_{\mathcal{P}}(p,q)^{-1}$, and $s(p,q) = c ||q||^{3/2}$ when $\epsilon ||q||^{-2} << 1$. Furthermore,

 $C_{\mathcal{P}}(p,q) \leq \tilde{C}_{\mathcal{P}}(p,q) := \max(\mu^{-1}||q||^{-1/2},\nu^{-1}||q||^{-1}).$ Consider $\hat{\delta}(t_n) = \delta(t_n)/(\tilde{C}_{\mathcal{P}}(y)\tilde{L}^2_{\mathcal{P}(y)})$, then compare $\frac{\max_n ||\hat{\delta}(t_n)||}{\min_n ||\hat{\delta}(t_n)||} = 1.29709, \quad \text{with} \quad \frac{\max_n ||\delta(t_n)||}{\min_n ||\delta(t_n)||} = 672.716$

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$$\frac{\max_{n} ||\hat{\delta}(t_{n})||}{\min_{n} ||\hat{\delta}(t_{n})||} = 1.29709, \quad \text{with} \quad \frac{\max_{n} ||\delta(t_{n})||}{\min_{n} ||\delta(t_{n})||} = 672.716.$$

A simple rule of thumb for the case of a

Motion in a central field

Consider $H(p,q) = \frac{1}{2}||p||^2 + V(||q||)$, where

$$V(r) = \sum_{j=-l}^{l} c_j r^j,$$

then set

$$s(q) = rac{||q||}{\sqrt{V^+(||q||)}}, \quad ext{where} \quad V^+(r) = \sum_{j=-l}^l |c_j| \, r^j.$$

When $V(r) = r^{\pm l}$, then it reduces to the recipe based on scaling invariance of Blanes and Budd (2004). When one term $r^{\pm l}$ clearly dominates in V(q), then both recipes give similar results.

A simple rule of thumb for the case of a

N-body problem

Consider $p_j, q_j \in \mathbb{R}^3$, $q = (q_1, \dots, q_N)$, and $p = (p_1, \dots, p_N)$, and

$$H(p,q) = \frac{1}{2} ||p||^2 + \sum_{i < j} V(r_{ij}),$$

where
$$r_{ij} = ||q_i - q_j||$$
 and $V(r) = \sum_{j=-l}^{l} c_j r^j$. Then set

$$s(q) = \left(\sum_{i < j} V^+(r_{ij})\right)^{-1/2} \left(\sum_{i < j} r_{ij}^{-2}\right)^{-1/2}$$

where $V^+(r) = \sum_{j=-l}^{l} |c_j| r^j$.

A variant of L(y) for $|| \cdot ||_{\infty}$ and for

Real analytic Hamiltonian systems

For each $y \in \mathbb{R}^{2d}$, for each invertible matrix \mathcal{P} consider

$$L_{\mathcal{P}}(y) = \max_{i,j} \left| \left(\mathcal{P}J^{-1}\mathcal{P}^{\mathsf{T}} \right)_{i,j} \right| \left(\max_{||\mathcal{P}(z-y)|| \leq 1} |\mathcal{H}(z)| \right)$$

then define

$$L(y) = \inf_{\mathcal{P}} L_{\mathcal{P}}(y).$$

Example (Perturbed Kepler with $s(q) = ||q||^{3/2}$)

For the Hamiltonian system

$$\mathcal{H}(p,q) = ||q||^{3/2} (\frac{1}{2} ||p||^2 + V(||q||) - H_0), \quad V(r) = \frac{1}{r} - \frac{\epsilon}{3r^3},$$

one can similarly obtain

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where $|\frac{1}{2}||p||^2 + V(||q||) - H_0| \le \delta$.

For $\epsilon = 0$ and $\delta = 0$ and $H_0 < 0$,

 $L_{\mathcal{P}}(p,q) \leq \sqrt{2}c_1 + c_2 \left(2(1+H_0||q||)\right)^{-1/2}.$

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Scaling invariance and adaptativity (Budd et al. 2003, ...)

If $\frac{d}{dt}y = f(y)$ is such that there exists a one-parameter family of invertible matrices Q_{λ} (for $\lambda \neq 0$) such that

 $\lambda f(Q_{\lambda}y) = Q_{\lambda}f(y),$

then the time reparametrization function s(y) should satisfy

 $s(Q_{\lambda}y) = \lambda s(y).$

Actually, for the original system,

$$L(Q_{\lambda}y) = \lambda^{-1}L(y),$$

and thus cannot be bounded for all y. The criterium based on the scaling invariance guarantees that, for $\hat{f}(y) = s(y)f(y)$, it holds that $\hat{L}(Q_{\lambda}y) = \hat{L}(y)$.