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Partitioned Methods for Multifield Problems

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Runge–Kutta methods

Consider

$$\dot{\mathbf{u}}(t) = \mathbf{f}(t, \mathbf{u}(t)), \quad \mathbf{u}(t_0) = \mathbf{u}_0$$

A Runge-Kutta method with s internal stages is given by

$$\mathbf{k}_i = \mathbf{f} \left(t_m + c_i \tau, \mathbf{u}_m + \tau \sum_{j=1}^s a_{ij} \mathbf{k}_j \right), \quad i = 1, \dots, s,$$

$$\mathbf{u}_{m+1} = \mathbf{u}_m + \tau \sum_{i=1}^s b_i \mathbf{k}_i.$$

The value s is called number of stages. The vector \mathbf{c} includes the grid points of the time discretisation and \mathbf{b} is vector with weights. The coefficients a_{ij} , b_i and c_i should be chosen in such a way that some order conditions are satisfied to obtain a sufficient consistency order.

Simplifying conditions

An s -stage Runge–Kutta method satisfies the simplifying conditions

$$B(p) : \sum_{i=1}^s b_i c_i^{k-1} = 1/k \quad k = 1, \dots, p,$$

$$C(q) : \sum_{j=1}^s a_{ij} c_j^{k-1} = c_i^k / k \quad i = 1, \dots, s, k = 1, \dots, q,$$

$$D(r) : \sum_{i=1}^s b_i c_i^{k-1} a_{ij} = b_j (1 - c_j^k) / k \quad j = 1, \dots, s, k = 1, \dots, r.$$

(see Butcher, 1964).

The simplifying conditions can be written in matrix-vector notation.

Remarks

- The condition $B(p)$ is equivalent to a quadrature rule with the nodes c_i and the weights b_i which integrates polynomials of degree $p - 1$ exact.
- The conditions $C(q)$ have the following meaning. The intermediate values \mathbf{k}_i are integrated exactly by a quadrature rule with the weights a_{ij} and the nodes c_i which integrates polynomials of degree q exactly.

Result

- An RK-method with s internal stages has the convergence order p , if the simplifying conditions $B(p)$, $C(l)$, and $D(m)$ with

$$p \leq \min\{l + m + 1, 2l + 2\}$$

are satisfied.

- There exists only one RK-method with s stages and with $p = 2s$. This method satisfies $B(2s)$, $C(s)$, and $D(s)$.

For the proof we refer to the book of Butcher.

Methods of order 2s

In the case of the Gauß quadrature rules the nodes c_i are chosen as the roots of the **shifted Legendre polynomial of degree s** , i.e.

$$P_s(2t - 1) = \frac{1}{s!} \frac{d^s}{dt^s} [t^s (t - 1)^s].$$

With respect to the **$L_2(0, 1)$ -scalar product**

$$\langle q, w \rangle := \int_0^1 q(t) w(t) dt$$

the polynomial $P_s(2t - 1)$ is orthogonal to all polynomials of degree $< s$, i.e. $\langle P_s, w \rangle = 0$ for all polynomials w of degree less than s . The roots of the Legendre polynomials P_s can be found in the book of Abramowitz and Stegun.

Methods of order 2s-2

nodes c_i are given by the roots of the polynomial

$$P_{s,\xi,\mu}(2x-1) = P_s(2x-1) + \xi P_{s-1}(2x-1) + \mu P_{s-2}(2x-1), \quad \xi, \mu \in \mathbb{R}.$$

Here the cases $\xi = 0$ and $\mu = 1$ are considered leading to the so-called Lobatto-III methods with $c_1 = 0$ and $c_s = 1$. The weights b_i are determined with $B(s)$ and the matrix A as follows:

- *Lobatto-IIIA* (see Ehle (1968)): with $C(s)$
- *Lobatto-IIIB* (see Ehle (1968)): with $D(s)$
- *Lobatto-IIIC* (see Chipman (1971)): with $C(s-1)$ and $a_{i1} = b_i$, $i = 1, \dots, s$.

Lobatto-IIIA methods

$$\begin{array}{c|cc} 0 & 0 & 0 \\ 1 & \frac{1}{2} & \frac{1}{2} \\ \hline & \frac{1}{2} & \frac{1}{2} \end{array}$$

$$\begin{array}{c|ccc} 0 & 0 & 0 & 0 \\ \frac{1}{2} & \frac{5}{24} & \frac{1}{3} & -\frac{1}{24} \\ 1 & \frac{1}{6} & \frac{2}{3} & \frac{1}{6} \\ \hline & \frac{1}{6} & \frac{2}{3} & \frac{1}{6} \end{array}$$

Lobatto-IIIB methods

$$\begin{array}{c|cc} 0 & \frac{1}{2} & 0 \\ 1 & \frac{1}{2} & 0 \\ \hline & \frac{1}{2} & \frac{1}{2} \end{array}$$

$$\begin{array}{c|ccc} 0 & \frac{1}{6} & -\frac{1}{6} & 0 \\ \frac{1}{2} & \frac{1}{6} & \frac{1}{3} & 0 \\ 1 & \frac{1}{6} & \frac{5}{6} & 0 \\ \hline & \frac{1}{6} & \frac{2}{3} & \frac{1}{6} \end{array}$$

Lobatto-IIIC methods

$$\begin{array}{c|cc} 0 & \frac{1}{2} & -\frac{1}{2} \\ 1 & \frac{1}{2} & \frac{1}{2} \\ \hline & \frac{1}{2} & \frac{1}{2} \end{array}$$

$$\begin{array}{c|ccc} 0 & \frac{1}{6} & -\frac{1}{3} & \frac{1}{6} \\ \frac{1}{2} & \frac{1}{6} & \frac{5}{12} & -\frac{1}{12} \\ 1 & \frac{1}{6} & \frac{2}{3} & \frac{1}{6} \\ \hline & \frac{1}{6} & \frac{2}{3} & \frac{1}{6} \end{array}$$

Prothero–Robinson example

Order results

method	local error	global error	
		τ const.	τ variable
Gauß (s odd)	τ^{s+1}	τ^{s+1}	τ^s
Gauß (s even)	τ^{s+1}	τ^s	τ^s
Radau IA	τ^s	τ^s	τ^s
Radau IIA	$z^{-1}\tau^{s+1}$	$z^{-1}\tau^{s+1}$	$z^{-1}\tau^{s+1}$
Lobatto IIIA (s odd)	$z^{-1}\tau^{s+1}$	$z^{-1}\tau^s$	$z^{-1}\tau^s$
Lobatto IIIA (s even)	$z^{-1}\tau^{s+1}$	$z^{-1}\tau^{s+1}$	$z^{-1}\tau^s$
Lobatto IIIB (s odd)	$z^{-1}\tau^{s-1}$	$z^{-1}\tau^{s-2}$	$z^{-1}\tau^{s-2}$
Lobatto IIIB (s even)	$z^{-1}\tau^{s-1}$	$z^{-1}\tau^{s-1}$	$z^{-1}\tau^{s-2}$
Lobatto IIIC	$z^{-1}\tau^s$	$z^{-1}\tau^s$	$z^{-1}\tau^s$

Coupled ODEs

Consider

$$\dot{\mathbf{u}} = \mathbf{f}(t, \mathbf{u}, \mathbf{v}), \quad \mathbf{u}(t_0) = \mathbf{u}_0,$$

$$\dot{\mathbf{v}} = \mathbf{g}(t, \mathbf{u}, \mathbf{v}), \quad \mathbf{v}(t_0) = \mathbf{v}_0$$

Examples:

- Second order systems such as mechanical systems
- coupled diffusion-reaction systems such as the Brusselator

A simplified model of a nuclear reactor

- Literature: Strehmel and Weiner, 1984
- $N(t)$... average density of neutrons
- $T_b(t)$... temperature of fuel
- $C_i(t)$... nuclear concentrations.
- system of ODEs:

$$\dot{N}(t) = \frac{1}{l} \left(\gamma(T_B(t) - T_B(0))N(t) + \sum_{i=1}^6 \beta_i(C_i(t) - N(t)) \right),$$

$$\dot{T}_B(t) = \frac{1}{C} (dN(t) - K(T_B(t) - T_M)),$$

$$\dot{C}_i(t) = \lambda_i(N(t) - C_i(t)), \quad i = 1, \dots, 6.$$

- quantities $\gamma, d, K, T_m, \beta_i, C, l$ and $\lambda_i \in [-3, 0)$ are given and independent from t .

Hamiltonian systems

Hamiltonian problems are ODEs of the form

$$\dot{\mathbf{p}} = -H_q(\mathbf{p}, \mathbf{q}) = -\frac{\partial H}{\partial \mathbf{q}}(\mathbf{p}, \mathbf{q}),$$

$$\dot{\mathbf{q}} = H_p(\mathbf{p}, \mathbf{q}) = \frac{\partial H}{\partial \mathbf{p}}(\mathbf{p}, \mathbf{q})$$

- $H(p_1, \dots, p_d, q_1, \dots, q_d)$... **Hamiltonian** (given function)
- The Hamiltonian represents the total energy.
- q_i ... position coordinates
- p_i ... momenta.
- $H(\mathbf{p}, \mathbf{q})$ is constant.

Movement of a pendulum

Pendulum of length 1: Consider

$$H(p, q) = \frac{1}{2}p^2 - \cos q.$$

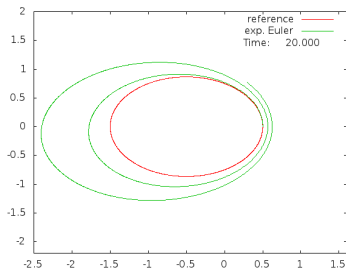
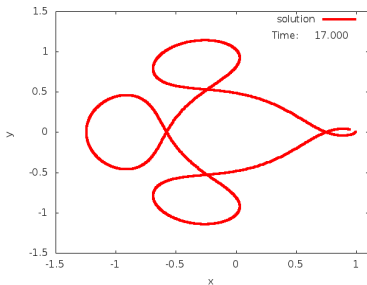
Then

$$\dot{p} = -\sin q,$$

$$\dot{q} = p$$

Further examples

- Keplers problem
- Arenstorf orbits
- movement of planets
- ...



Partitioned Runge–Kutta methods

$$\mathbf{k}_i = \mathbf{f} \left(t_m + c_i \tau, \mathbf{u}_m + \tau \sum_{j=1}^s a_{ij} \mathbf{k}_j, \mathbf{v}_m + \tau \sum_{j=1}^s \hat{a}_{ij} \mathbf{l}_j \right)$$

$$\mathbf{l}_i = \mathbf{g} \left(t_m + \hat{c}_i \tau, \mathbf{u}_m + \tau \sum_{j=1}^s a_{ij} \mathbf{k}_j, \mathbf{v}_m + \tau \sum_{j=1}^s \hat{a}_{ij} \mathbf{l}_j \right)$$

$$\mathbf{u}_{m+1} = \mathbf{u}_m + \tau \sum_{i=1}^s b_i \mathbf{k}_i, \quad \mathbf{v}_{m+1} = \mathbf{v}_m + \tau \sum_{i=1}^s \hat{b}_i \mathbf{l}_i.$$

- **Coefficients:** a_{ij} , b_i , c_i , \hat{a}_{ij} , \hat{b}_i , \hat{c}_i
- **Advantage:** Each problem can be solved by a special Runge–Kutta method.

Application

Second order ODE written as first order:

$$\dot{\mathbf{u}} = \mathbf{v}, \quad \mathbf{v}(t_0) = \mathbf{v}_0,$$

$$\dot{\mathbf{v}} = \mathbf{f}(t, \mathbf{u}, \mathbf{v}), \quad \mathbf{u}(t_0) = \mathbf{u}_0$$

Apply partitioned Runge–Kutta method:

$$\mathbf{k}_i = \mathbf{v}_m + \tau \sum_{j=1}^s \hat{a}_{ij} \mathbf{l}_j$$

$$\mathbf{l}_i = \mathbf{f} \left(t_m + c_i \tau, \mathbf{u}_m + \tau \sum_{j=1}^s a_{ij} \mathbf{k}_j, \mathbf{v}_m + \tau \sum_{j=1}^s \hat{a}_{ij} \mathbf{l}_j \right)$$

$$= \mathbf{f} \left(t_m + c_i \tau, \mathbf{u}_m + \tau \sum_{j=1}^s a_{ij} \left(\mathbf{v}_m + \tau \sum_{k=1}^s \hat{a}_{jk} \mathbf{l}_k \right), \mathbf{v}_m + \tau \sum_{j=1}^s \hat{a}_{ij} \mathbf{l}_j \right)$$

Runge–Kutta–Nyström method

A Runge–Kutta–Nyström method can then be written as

$$\mathbf{l}_i = \mathbf{f} \left(t_m + c_i \tau, \mathbf{u}_m + \tau c_i \mathbf{v}_m + \tau^2 \sum_{j=1}^s \bar{a}_{ij} \mathbf{l}_j, \mathbf{v}_m + \tau \sum_{j=1}^s \hat{a}_{ij} \mathbf{l}_j \right)$$

$$\mathbf{u}_{m+1} = \mathbf{u}_m + \tau \mathbf{v}_m + \tau^2 \sum_{i=1}^s \bar{b}_i \mathbf{l}_i$$

$$\mathbf{v}_{m+1} = \mathbf{v}_m + \tau \sum_{i=1}^s \hat{b}_i \mathbf{l}_i.$$

where

$$\bar{a}_{ij} = \sum_{k=1}^s a_{ij} \hat{a}_{jk}, \quad \bar{b}_i = b_i \sum_{j=1}^s \hat{a}_{ij}$$

Example

Nyström method of order 4:

	0			
c_i	1/2	1/8		\bar{a}_{ij}
	1	0	1/2	
\hat{b}_i		1/6	1/3	0
\bar{b}_i		1/6	4/6	1/6

Example

Advantage: ODE can be splitted into a stiff and into a non-stiff part.
Consider

$$\begin{pmatrix} \dot{u}_1 \\ \dot{u}_2 \end{pmatrix} = \begin{pmatrix} -81 & -34 \\ -38 & -24 \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \end{pmatrix}, \quad \begin{pmatrix} u_1(0) \\ u_2(0) \end{pmatrix} = \begin{pmatrix} 1 \\ 3 \end{pmatrix}.$$

Exact solution:

$$\begin{pmatrix} u_1(t) \\ u_2(t) \end{pmatrix} = \begin{pmatrix} 2 \\ 1 \end{pmatrix} \exp(-100t) + \begin{pmatrix} -1 \\ 2 \end{pmatrix} \exp(-5t).$$

Methods

- method of Heun:

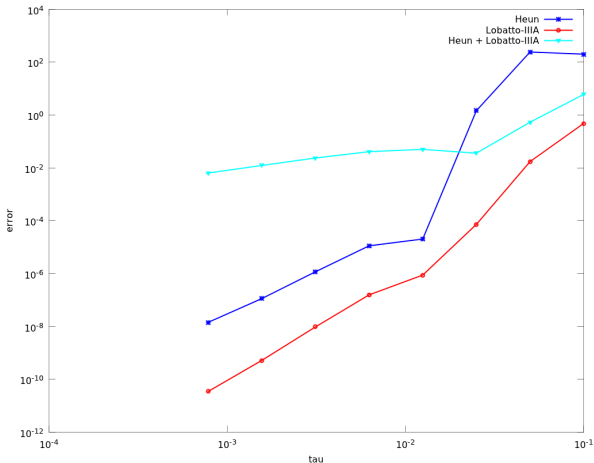
$$\begin{array}{c|ccc} 0 & & & \\ \frac{1}{3} & \frac{1}{3} & & \\ \frac{2}{3} & 0 & \frac{2}{3} & \\ \hline \frac{3}{3} & \frac{1}{4} & 0 & \frac{3}{4} \end{array}$$

- Lobatto-IIIA method with 3 internal stages

$$\begin{array}{c|ccc} 0 & 0 & 0 & 0 \\ \frac{1}{2} & \frac{5}{24} & \frac{1}{3} & -\frac{1}{24} \\ 1 & \frac{1}{6} & \frac{2}{3} & \frac{1}{6} \\ \hline & \frac{1}{6} & \frac{2}{3} & \frac{1}{6} \end{array}$$

- partitioned Runge–Kutta method with the Heun and Lobatto-IIIA method.

Numerical result



Remarks

- Partitioned Runge–Kutta methods may have order reduction.
- Higher order PRK methods must satisfy further order conditions
- A partitioned Runge–Kutta method is of order 2, if and only if both Runge–Kutta methods have at least order 2 and if the coupling condition

$$\sum_{i,j=1}^s b_i \hat{a}_{ij} = \sum_{i,j=1}^s \hat{b}_i a_{ij} = \frac{1}{2}$$

is satisfied.

- This condition is valid, if $c_j = \hat{c}_j$, $b_j = \hat{b}_j$, and both methods satisfy the condition

$$c_j = \sum_{j=1}^s a_{ij}$$

New method

Aim: Find an explicit Runge–Kutta method of order 3 with

$$c_1 = 0, \quad c_2 = 1/2, \quad c_3 = 1$$

$$b_1 = 1/6, \quad b_2 = 2/3, \quad b_3 = 1/6.$$

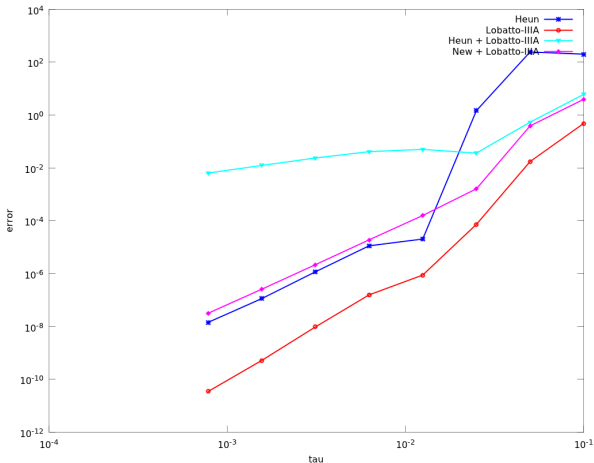
remaining order condition

$$\sum_{i=1}^s b_i a_{ij} c_j = 1/6$$

is valid, if we choose $\alpha_{32} = 2$. Finally we have $\alpha_{31} = -1$.

$$\begin{array}{c|ccc} 0 & & & \\ \frac{1}{2} & \frac{1}{2} & & \\ 1 & -1 & 2 & \\ \hline & \frac{1}{6} & \frac{4}{6} & \frac{1}{6} \end{array}$$

Numerical result



Literature

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- S. Skelboe: [Stability properties of backward differentiation multirate formulas.](#) Appl. Numer. Math. 5(1-2):151-160, 1989.
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- R. D. Skeel. [Waveform iteration and the shifted Picard splitting.](#) Sci. Stat. Comput., 10(4):756–776, 1989.

Dynamic iteration methods

- Let us start with the coupled system of ODEs given by

$$\begin{aligned}\dot{\mathbf{u}} &= \mathbf{f}(t, \mathbf{u}, \mathbf{v}), & \mathbf{u}(0) &= \mathbf{u}_0 \\ \dot{\mathbf{v}} &= \mathbf{g}(t, \mathbf{u}, \mathbf{v}), & \mathbf{v}(0) &= \mathbf{v}_0.\end{aligned}$$

- As in the case of stationary problems a splitting can be introduced.
- In the case of dynamic problem this approach is called **waveform relaxation** (WR).
- We have the same partitioned methods as in the case of linear/non-linear systems, i.e. Jacobi, Gauß–Seidel, and SOR.

Jacobi WR method

- Jacobi WR method:

$$\dot{\mathbf{u}}^{(k+1)} = \mathbf{f}(t, \mathbf{u}^{(k+1)}, \mathbf{v}^{(k)})$$

$$\dot{\mathbf{v}}^{(k+1)} = \mathbf{g}(t, \mathbf{u}^{(k)}, \mathbf{v}^{(k+1)})$$

- As in the case of stationary problems both ODEs can be solved in parallel independently from each other.
- The communication of the two solvers is needed only at the end of each timestep.

SOR WR method

SOR WR method:

$$\dot{\tilde{\mathbf{u}}}^{(k+1)} = \mathbf{f}(t, \tilde{\mathbf{u}}^{(k+1)}, \mathbf{v}^{(k)}), \quad \tilde{\mathbf{u}}^{(k+1)}(0) = \mathbf{u}_0$$

$$\dot{\tilde{\mathbf{v}}}^{(k+1)} = \mathbf{g}(t, \tilde{\mathbf{u}}^{(k+1)}, \tilde{\mathbf{v}}^{(k+1)}), \quad \tilde{\mathbf{v}}^{(k+1)}(0) = \mathbf{v}_0$$

$$\mathbf{u}^{(k+1)} = \omega \tilde{\mathbf{u}}^{(k+1)} + (1 - \omega) \mathbf{u}^{(k)}$$

$$\mathbf{v}^{(k+1)} = \omega \tilde{\mathbf{v}}^{(k+1)} + (1 - \omega) \mathbf{v}^{(k)}.$$

For $\omega = 1$ we get the **Gauß–Seidel WR method**.

Convergence in the linear case

$$\dot{\mathbf{u}} + A\mathbf{u} = \mathbf{f}(t), \quad \mathbf{u}(0) = \mathbf{u}_0 \quad (1)$$

Splitting $A = M - N$:

$$\dot{\mathbf{u}}^{(k+1)} + M\mathbf{u}^{(k+1)} = N\mathbf{u}^{(k)} + \mathbf{f}(t), \quad \mathbf{u}^{(k)}(0) = \mathbf{u}_0 \quad (2)$$

Let $\mathcal{K} : \mathbf{v} \mapsto \mathbf{u}$ be a linear integral operator given by

$$\mathcal{K}\mathbf{u}(t) = \int_0^t e^{(s-t)M} N\mathbf{u}(s) ds.$$

Then the solution of (??) can be written as

$$\mathbf{u}^{(k+1)} = \mathcal{K}\mathbf{u}^{(k)} + \varphi$$

with

$$\varphi(t) = e^{-tM} \mathbf{u}_0 + \int_0^t e^{(s-t)M} \mathbf{f}(s) ds. \quad (3)$$

Convergence in the linear case

Let X be a Banach space and assume that \mathcal{K} is a bounded operator in X . For the convergence we need that spectral radius of \mathcal{K}

$$\rho(\mathcal{K}) := \lim_{k \rightarrow \infty} \|\mathcal{K}^k\|^{1/k}$$

satisfies $\rho(\mathcal{K}) < 1$, since $\mathbf{f} \in X$ implies $\varphi \in X$. In the following we are interested in the uniform convergence on a long but bounded time interval.

Convergence in the linear case

First we want to show that $\rho(\mathcal{K}) = 0$ in the space of uniform convergence in $[0, T]$. We have

$$|\mathcal{K}\varphi(t)| \leq C \int_0^t |\varphi(s)| ds \leq Ct \|\varphi\|_\infty$$

with $C = \exp(T\|M\|)\|N\|$, where $\|\cdot\|$ denotes a norm in \mathbb{C}^n . It follows

$$|\mathcal{K}^j \varphi(t)| \leq C^j \frac{t^j}{j!} \|\varphi\|_\infty$$

and

$$\left\| \left(1 - \frac{1}{\lambda} \mathcal{K} \right)^{-1} \right\| = \left\| \sum_{j=0}^{\infty} \left(\frac{1}{\lambda} \mathcal{K} \right)^j \right\| \leq \sum_{j=0}^{\infty} \left(\frac{CT}{\lambda} \right)^j \frac{1}{j!} = \exp \left(\frac{CT}{\lambda} \right)$$

for all $\lambda \neq 0$.

Convergence in the linear case

- If $\rho(\mathcal{K}) = 0$ then no effect of the splitting on the actual rate of convergence can be observed.
- Therefore use the weighted norm

$$\|\mathbf{u}\| := \sup_{t \in [0, T]} \|\exp(-\alpha t) \mathbf{u}(t)\|$$

in which \mathcal{K} becomes a contraction.

- A similar estimate as above holds for the weighted space.
- Find estimates, which are independent of the length of the interval.
- Consider Banach spaces on $[0, \infty)$. Let X denote any usual L^p -space of \mathbb{C}^n -valued functions defined on $[0, \infty)$.

Theorem

Let $X = L^p(\mathbb{R}_+, \mathbb{C}^n)$ with $1 \leq p \leq \infty$.

1. Then $\varphi \in X$ is implied by $\mathbf{f} \in X$, if and only if all eigenvalues of M have positive real part.
2. If all eigenvalues of A have positive real parts then \mathcal{K} is a bounded operator in X if and only if the eigenvalues of M have positive real parts.

Proof

We want to show, that

$$\left(\int_0^\infty |\varphi(s)|^p ds \right)^{1/p} < \infty$$

holds. From equation

$$\varphi(t) = e^{-tM} \mathbf{u}_0 + \int_0^t e^{(s-t)M} \mathbf{f}(s) ds.$$

we have

$$\left(\int_0^\infty \left| e^{-sM} \mathbf{u}_0 + \int_0^s e^{(\tau-s)M} \mathbf{f}(\tau) d\tau \right|^p ds \right)^{1/p} < \infty$$

Theorem

- Let $X = L^p(\mathbb{R}_+, \mathbb{C}^n)$ with $1 \leq p \leq \infty$.
- Assume that all eigenvalues of M have positive real part.
- Then

$$\rho(\mathcal{K}) = \max_{\xi \in \mathbb{R}} \rho((i\xi I + M)^{-1} N).$$

- Note, that ρ in the left-hand side is the spectral radius of the operator
- Note, that ρ in the right-hand side is the spectral radius of the matrix.

Jacobi overrelaxation (JOR) WR method

- **decomposition:** $A = D - L - U$
- **Splitting:**

$$A = M - N = \frac{1}{\omega}D - \left(\frac{1-\omega}{\omega}D + L + U \right).$$

- For $\omega = 1$ we have the usual Jacobi WR method.
- Let $J(0) = D^{-1}(L + U)$ be the **Jacobi matrix**.
- **Theorem:** For any H-matrix A with $D > 0$ and $M(A)$ a nonsingular M-matrix the dynamic JOR WR method converges whenever

$$0 < \omega < \frac{2}{1 + \rho(|J(0)|)}.$$

SOR WR method

- Splitting:

$$A = M - N = \left(\frac{1}{\omega} D - L \right) - \left(\frac{1 - \omega}{\omega} D + U \right).$$

- **Theorem:** For any H-matrix A with $D > 0$ and $M(A)$ a nonsingular M-matrix the SOR WR method converges whenever

$$0 < \omega < \frac{2}{1 + \rho(|J(0)|)}.$$

Symmetric SOR (SSOR) WR method

Consider methods that involve two different phases. Therefore let

$$\begin{aligned}\dot{\mathbf{u}}^{(k+1/2)} + M_1 \mathbf{u}^{(k+1/2)} &= N_1 \mathbf{u}^{(k)} + \mathbf{g}_1 \\ \dot{\mathbf{u}}^{(k+1)} + M_2 \mathbf{u}^{(k+1)} &= N_2 \mathbf{u}^{(k+1/2)} + \mathbf{g}_2 \\ \mathbf{u}^{(k+1)}(0) &= \mathbf{u}^{(k+1/2)}(0) = \mathbf{u}_0.\end{aligned}$$

For the **symmetric SOR (SSOR) WR method** we have

$$\begin{aligned}M_1 &= \frac{1}{\omega} D - L, & N_1 &= \frac{1 - \omega}{\omega} D + U, \\ M_2 &= \frac{1}{\omega} D - U, & N_2 &= \frac{1 - \omega}{\omega} D + L.\end{aligned}$$

Symmetric SOR (SSOR) WR method

For any H-matrix A with $D > 0$ and $M(A)$ a nonsingular M-matrix the symmetric SOR WR method converges whenever

$$0 < \omega < \frac{2}{1 + \rho(|J(0)|)}.$$

Example

Let

$$A = \begin{pmatrix} 1 & -\lambda \\ \lambda & 1 \end{pmatrix}, \quad \lambda \in (0, 1).$$

Let us now check the assumptions from the Theorems.

- We have $D = I > 0$.
- A is an H-matrix, i.e. $M(A)$ is a M-matrix, since

$$M(A) = \begin{pmatrix} 1 & -\lambda \\ -\lambda & 1 \end{pmatrix}.$$

It follows

$$[M(A)]^{-1} = \frac{1}{1 - \lambda^2} \begin{pmatrix} 1 & \lambda \\ \lambda & 1 \end{pmatrix}.$$

Example

- Moreover we have

$$J(0) = D^{-1}(L + U) = L + U = \begin{pmatrix} 0 & \lambda \\ -\lambda & 0 \end{pmatrix}$$

- $\rho(|J(0)|) = \lambda < 1$.
- The condition

$$0 < \omega < \frac{2}{1 + \lambda}$$

is satisfied for all $\lambda \in (0, 1)$.

Example

Let

$$A = (n+1)^2 \begin{pmatrix} -2 & 1 & & & \\ 1 & -2 & 1 & & \\ & \ddots & \ddots & \ddots & \\ & & 1 & -2 & 1 \\ & & & 1 & -2 \end{pmatrix} \in \mathbb{R}^{n,n}.$$

Then A is a H-matrix with $D > 0$.

A model problem

Let us consider the ODE

$$\dot{\mathbf{u}} + Q\mathbf{u} = 0, \quad \mathbf{u}(0) = \mathbf{u}_0$$

with

$$Q = \begin{pmatrix} 1 & -\lambda \\ \lambda & 1 \end{pmatrix}.$$

First we solve this ODE with explicit Euler method. In this case we get

$$\mathbf{u}_{m+1} = \mathbf{u}_m - \tau Q\mathbf{u}_m = (I - \tau Q)\mathbf{u}_m.$$

Our numerical solution is stable, if the spectral radius $\rho(I - \tau Q) < 1$.

The eigenvalues of $I - \tau Q$ are given by

$$\lambda_{1,2} = 1 - \tau \pm i\tau\lambda$$

and this implies $\tau < 2/(1 + \lambda^2)$, i. e. we get a stepsize restriction.

A model problem

Apply implicit Euler method:

$$\mathbf{u}_{m+1} = (I + \tau Q)^{-1} \mathbf{u}_m.$$

The numerical solution is stable, if the absolute values of the eigenvalues of the matrix $(I + \tau Q)^{-1}$ are bounded by one. The eigenvalues are given by

$$\frac{1 + \tau \pm i\tau\lambda}{(1 + \tau)^2 + (\tau\lambda)^2}.$$

A model problem

Apply Gauß–Seidel WR method:

$$\dot{\mathbf{u}}^{(k+1)} + M\mathbf{u}^{(k+1)} = N\mathbf{u}^{(k)},$$

where

$$M = D - L = \begin{pmatrix} 1 & -\lambda \\ 0 & 1 \end{pmatrix}, \quad N = U = \begin{pmatrix} 0 & 0 \\ -\lambda & 0 \end{pmatrix}.$$

If we use the explicit Euler method, we obtain

$$\mathbf{u}_{m+1}^{(k+1)} = \mathbf{u}_m^{(k+1)} + \tau \left[N\mathbf{u}_m^{(k)} - M\mathbf{u}_m^{(k+1)} \right].$$

A model problem

In each timestep we iterate w. r. t. k until convergence. Then

$$\mathbf{u}_m^{(k+1)} = \mathbf{u}_m^{(k)} = \mathbf{u}_m.$$

Then it follows

$$\mathbf{u}_{m+1}^{(k+1)} = \mathbf{u}_m + \tau [\mathbf{N}\mathbf{u}_m - \mathbf{M}\mathbf{u}_m] = (\mathbf{I} - \tau\mathbf{Q})\mathbf{u}_m,$$

which is the same approximation as in the monolythical approach.

A model problem

Apply Gauß–Seidel WR method and the implicit Euler method:

$$\mathbf{u}_{m+1}^{(k+1)} = \mathbf{u}_m + \tau \left[N\mathbf{u}_{m+1}^{(k)} - M\mathbf{u}_{m+1}^{(k+1)} \right].$$

It follows

$$\mathbf{u}_{m+1}^{(k+1)} = (I + \tau M)^{-1} \mathbf{u}_m + \tau (I + \tau M)^{-1} N \mathbf{u}_{m+1}^{(k)}.$$

For the matrix $\tau(I + \tau M)^{-1} N$ we have

$$\tau(I + \tau M)^{-1} N = \begin{pmatrix} \frac{-(\tau\lambda)^2}{(1 - \tau)^2} & 0 \\ \frac{\tau\lambda}{1 - \tau} & 0 \end{pmatrix},$$

which has the eigenvalues 0 and $\frac{-(\tau\lambda)^2}{(1 - \tau)^2}$. The Gauß–Seidel WR method converges, if $\tau < 1/(1 + \lambda)$.

A model problem

Apply Runge–Kutta method on model problem:

$$\mathbf{k}_i^{(k+1)} = N \left(\mathbf{u}_m^{(k)} + \tau \sum_{j=1}^s a_{ij} \mathbf{k}_j^{(k)} \right) - M \left(\mathbf{u}_m^{(k)} + \tau \sum_{j=1}^s a_{ij} \mathbf{k}_j^{(k+1)} \right).$$

With $Q = M - N$ it follows

$$\begin{pmatrix} I + \tau M a_{11} & \dots & \tau M a_{1s} \\ \vdots & \ddots & \vdots \\ \tau M a_{s1} & \dots & I + \tau M a_{ss} \end{pmatrix} \begin{pmatrix} \mathbf{k}_1^{(k+1)} \\ \vdots \\ \mathbf{k}_s^{(k+1)} \end{pmatrix} = \begin{pmatrix} -Q \mathbf{u}_m \\ \vdots \\ -Q \mathbf{u}_m \end{pmatrix} + \tau N \begin{pmatrix} \sum_{j=1}^s a_{1j} \mathbf{k}_j^{(k)} \\ \vdots \\ \sum_{j=1}^s a_{sj} \mathbf{k}_j^{(k)} \end{pmatrix}$$

A model problem

Next we introduce the setting $\mathbf{k} := (\mathbf{k}_1, \dots, \mathbf{k}_s)^\top$ and $A = (a_{ij})_{i,j=1}^s$ and get with the Kronecker product

$$(I + \tau(A \otimes M)) \mathbf{k}_i^{(k+1)} = -(Q \otimes \mathbf{e}) \mathbf{u}_m + \tau(A \otimes N) \mathbf{k}_j^{(k)}.$$

Next we need the eigenvalues of the matrix

$$\tau (I + \tau(A \otimes M))^{-1} (A \otimes N),$$

Implementation

We start our considerations with the PDE

$$\dot{u} - u'' = -e^{-t}(x^2 + 2), \quad \text{in } (0, \bar{t}] \times (0, 1). \quad (4)$$

The Dirichlet boundary and the initial conditions are taken from the exact solution, which is given by

$$u(t, x) = 1 + e^{-t}x^2.$$

The space discretisation is done with central differences, i. e. we have

$$u''(t, x) \approx \frac{1}{h^2} [u(t, x + h) + u(t, x - h) - 2u(t, x)].$$

Implementation

Finally we get the MOL-ODE

$$\dot{\mathbf{u}} + \mathbf{A}\mathbf{u} = \mathbf{f} \quad (5)$$

with

$$\mathbf{A} = \frac{1}{h^2} \begin{pmatrix} -2 & 1 & & & & \\ 1 & -2 & 1 & & & \\ & \ddots & \ddots & \ddots & & \\ & & & 1 & -2 & 1 \\ & & & & 1 & -2 \end{pmatrix},$$
$$\mathbf{f}(t) = -e^{-t} \begin{pmatrix} x_1^2 + 2 \\ x_2^2 + 2 \\ \vdots \\ x_{n-1}^2 + 2 \\ x_n^2 + 2 \end{pmatrix} + \frac{1}{h^2} \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \\ 1 + e^{-t} \end{pmatrix}.$$

Splitting

Next we apply the splitting $A = M - N$ and get

$$\dot{\mathbf{u}}^{(k+1)} + M\mathbf{u}^{(k+1)} = N\mathbf{u}^{(k)} + \mathbf{f}. \quad (6)$$

For the time discretisation of the MOL-ODE we use diagonally implicit Runge–Kutta methods. We choose the L-stable implicit Euler method, the trapezoidal rule (order 2, implicit, A-stable) and the method DIRK2 given by the Butcher table

$$\begin{array}{c|cc} \gamma & \gamma & 0 \\ 1 & 1-\gamma & \gamma \\ \hline & 1-\gamma & \gamma \end{array}, \quad \gamma = 1 - \sqrt{1/2} \approx 0,29.$$

The method is implicit, of second order and L-stable.

Discrete WR method

The discrete WR method is given by

$$\mathbf{k}_i^{(k+1)} = \mathbf{f}(t_m + c_i\tau) - (M - N)\mathbf{u}_m - \tau \sum_{j=1}^s a_{ij} \left(M\mathbf{k}_j^{(k+1)} - N\mathbf{k}_j^{(k)} \right), \quad k$$

$$\mathbf{u}_{m+1}^{(k+1)} = \mathbf{u}_m + \tau \sum_{i=1}^s b_i \mathbf{k}_i^{(k+1)}.$$

The symmetric SOR WR method is then given by

$$\dot{\mathbf{u}}^{(k+1/2)} + M_1 \mathbf{u}^{(k+1/2)} = N_1 \mathbf{u}^{(k)} + \mathbf{g}_1$$

$$\dot{\mathbf{u}}^{(k+1)} + M_2 \mathbf{u}^{(k+1)} = N_2 \mathbf{u}^{(k+1/2)} + \mathbf{g}_2.$$

Application

Applying the RK method on the symmetric SOR WR method gives us

$$\mathbf{k}_i^{(k+1/2)} = \mathbf{g}_1(t_m + c_i\tau) - (M_1 - N_1)\mathbf{u}_m - \tau \sum_{j=1}^s a_{ij} \left(M_1 \mathbf{k}_j^{(k+1/2)} - N_1 \mathbf{k}_j^{(k)} \right),$$

$$\mathbf{k}_i^{(k+1)} = \mathbf{g}_2(t_m + c_i\tau) - (M_2 - N_2)\mathbf{u}_m - \tau \sum_{j=1}^s a_{ij} \left(M_2 \mathbf{k}_j^{(k+1)} - N_2 \mathbf{k}_j^{(k+1/2)} \right),$$

$$\mathbf{u}_{m+1}^{(k+1)} = \mathbf{u}_m + \tau \sum_{i=1}^s b_i \mathbf{k}_i^{(k+1)}.$$

Results

First we apply the SOR WR method with $\omega = 1$. The central differences are applied with $h = 1/10$. Then we get the following numerical results:

	impl. Euler	trap. rule	DIRK2
$\tau = 0.100$	6.99e-04 (70)	1.62e-05 (50)	8.59e-05 (42)
$\tau = 0.050$	3.89e-04 (47)	3.72e-06 (32)	2.11e-05 (26)
$\tau = 0.025$	2.07e-04 (30)	9.13e-07 (20)	5.63e-06 (17)
$\tau = 0.013$	1.13e-04 (19)	2.31e-07 (13)	1.49e-06 (12)

Results

For $h = 1/100$ the following results are obtained

	impl. Euler	trap. rule	DIRK2
$\tau = 0.100$	1.98e-03 (1500)	2.94e-04 (1500)	1.45e-04 (1500)
$\tau = 0.050$	6.18e-04 (1500)	9.18e-06 (1500)	1.98e-05 (1450)
$\tau = 0.025$	2.10e-04 (1500)	2.35e-06 (978)	4.87e-06 (778)
$\tau = 0.013$	1.15e-04 (899)	3.13e-06 (518)	1.83e-06 (406)

Results

Next we compute the optimal ω_{opt} , which is given by

$$\omega_{opt} = 4/(4 - \mu^2), \text{ where } \mu = \rho(J(0)) = \rho(D^{-1}(L + U)) \approx 0.99951.$$

Then $\omega_{opt} \approx 1.3329$. Then we have for the SOR WR method

	impl. Euler	trap. rule	DIRK2
$\tau = 0.100$	7.39e-04 (1500)	1.25e-05 (1500)	8.39e-05 (1380)
$\tau = 0.050$	3.77e-04 (1500)	2.20e-06 (964)	2.04e-05 (780)
$\tau = 0.025$	2.02e-04 (894)	8.10e-07 (534)	5.24e-06 (420)
$\tau = 0.013$	1.12e-04 (495)	1.44e-06 (285)	1.34e-06 (222)

Results

symmetric SOR method

	impl. Euler	trap. rule	DIRK2
$\tau = 0.100$	6.74e-04 (1252)	1.49e-05 (870)	8.42e-05 (729)
$\tau = 0.050$	3.76e-04 (810)	2.85e-06 (514)	2.06e-05 (412)
$\tau = 0.025$	2.01e-04 (478)	2.79e-07 (283)	5.39e-06 (221)
$\tau = 0.013$	1.10e-04 (264)	5.74e-07 (151)	1.28e-06 (116)

Convergence analysis

For the "monolythical" Runge–Kutta method we have

$$\mathbf{k}_i = \mathbf{f}(t_m + c_i\tau) - (M - N)\mathbf{u}_m - \tau \sum_{j=1}^s a_{ij}(M - N)\mathbf{k}_j$$

and for the discrete WR method we have

$$\mathbf{k}_i^{(k+1)} = \mathbf{f}(t_m + c_i\tau) - (M - N)\mathbf{u}_m - \tau \sum_{j=1}^s a_{ij} \left(M\mathbf{k}_j^{(k+1)} - N\mathbf{k}_j^{(k)} \right).$$

Local error

The local error of the internal stages can be computed via

$$\begin{aligned}\epsilon_i^{(k+1)} &:= \mathbf{k}_i^{(k+1)} - \mathbf{k}_i \\ &= \tau \sum_{j=1}^s a_{ij} N \epsilon_j^{(k)} - \tau \sum_{j=1}^s a_{ij} M \epsilon_j^{(k+1)}.\end{aligned}$$

With the help of the Kronecker product we obtain

$$\epsilon^{(k+1)} = \tau(A \otimes N) \epsilon^{(k)} - \tau(A \otimes M) \epsilon^{(k+1)}.$$

It follows

$$\epsilon^{(k+1)} = \tau(I + \tau(A \otimes M))^{-1} (A \otimes N) \epsilon^{(k)}$$

Convergence analysis

- By C we denote we matrix $C := (I + \tau(A \otimes M))^{-1}(A \otimes N)$.
- numerical method converges, if $\tau < 1/\rho(C)$.
- implicit Euler method: $C := (I + \tau M)^{-1}N$
- trapezoidal rule: $C := \frac{1}{2}(I + \tau/2M)^{-1}N$.
- trapezoidal rule converges faster than the implicit Euler method.

Literature

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