Multirate explicit stabilized method in mixed precision arithmetic

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Table of Contents



- Introduction and motivation to mixed-precision arithmetic,
- Mixed precision explicit stabilized methods,
- Mixed precision multirate explicit stabilized methods.

Motivating Mixed-Precision Arithmetic



Mixed-precision algorithms combine low- and high-precision computations in order to benefit from:

- Performance, energy, and memory gains of low-precision,
- Accuracy of high-precision.

Format	unit roundoff u
bfloat16 (half)	$2^{-8} \approx 3.91 \times 10^{-3}$
fp16 (half)	$2^{-11} \approx 4.88 \times 10^{-4}$
fp32 (single)	$2^{-24} \approx 5.96 \times 10^{-8}$
fp64 (double)	$2^{-53} \approx 1.11 \times 10^{-16}$

Trend: roundoff unit *u* is getting larger!!!



Assumptions, computational setup, and notation:

- Computations in high-precision arithmetic are assumed to be exact.
- u is the roundoff unit of the low-precision format: $u \approx 10^{-3}$.
- Round to nearest.
- Computations performed in low precision are denoted by a hat $\widehat{\ }$, the error model is:

$$\widehat{a \operatorname{op} b} = (1 + \delta)(a \operatorname{op} b), \quad |\delta| < u, \quad \operatorname{op} \in \{+, -, *, /\},$$

Remember: $\widehat{}$ produces a relative error $\approx u \approx 10^{-3}$.



Motivating example on a linear problem

Consider

$$y' = Ay, \qquad y(0) = y_0$$

and the integrators

For accuracy

$$y_1 = y_0 + \Delta t A y_0,$$

 $y_1 = y_0 + \Delta t A y_0 + \frac{1}{2} \Delta t^2 A^2 y_0,$
 $y_1 = y_0 + \Delta t A y_0 + c \Delta t^2 A^2 y_0.$
For stability

Goal: design mixed-precision versions of these integrators preserving the original accuracy.

For $y_1 = y_0 + \Delta t A y_0$:

Try 1:

$$\widehat{y}_1 = \widehat{y_0 + \Delta t A y_0} = (1 + \delta)(y_0 + \Delta t A y_0)$$
$$= y_0 + \Delta t A y_0 + \mathcal{O}(u).$$

Local error: $\mathcal{O}(u)$.

Global error: $\mathcal{O}(u\Delta t^{-1})$.

Divergence



Motivating example on a linear problem

Consider

$$y' = Ay, \qquad y(0) = y_0$$

and the integrators

$$y_1 = y_0 + \Delta t A y_0,$$

$$y_1 = y_0 + \Delta t A y_0 + \frac{1}{2} \Delta t^2 A^2 y_0,$$

$$y_1 = y_0 + \Delta t A y_0 + c \Delta t^2 A^2 y_0.$$

Goal: design mixed-precision versions of these integrators preserving the original accuracy.

For $y_1 = y_0 + \Delta t A y_0$:

Try 2:

$$\widehat{y}_1 = y_0 + \Delta t \widehat{Ay_0} = y_0 + \Delta t A y_0 + \mathcal{O}(\Delta t u || A || || y_0 ||)$$

$$= y_0 + \Delta t A y_0 + \mathcal{O}(\Delta t u).$$
Local error: $\mathcal{O}(\Delta t u)$

Local error: $\mathcal{O}(\Delta tu)$.

Global error: $\mathcal{O}(u)$.

Saturation



Motivating example on a linear problem

Consider

$$y' = Ay, \qquad y(0) = y_0$$

and the integrators

$$y_1 = y_0 + \Delta t A y_0,$$

$$y_1 = y_0 + \Delta t A y_0 + \frac{1}{2} \Delta t^2 A^2 y_0,$$

$$y_1 = y_0 + \Delta t A y_0 + c \Delta t^2 A^2 y_0.$$

Goal: design mixed-precision versions of these integrators preserving the original accuracy.

For
$$y_1 = y_0 + \Delta t A y_0 + \frac{1}{2} \Delta t^2 A^2 y_0$$
:

Try 3:
For accuracy

$$\widehat{y}_{1} = y_{0} + \Delta t A y_{0} + \frac{1}{2} \Delta t^{2} \widehat{A^{2} y_{0}}$$

$$= y_{0} + \Delta t A y_{0} + \frac{1}{2} \Delta t^{2} A^{2} y_{0} + \mathcal{O}(\Delta t^{2} u).$$

Local error: $\mathcal{O}(\Delta t^2 u)$.

Global error: $\mathcal{O}(\Delta tu)$.

Order reduction



Motivating example on a linear problem

Consider

$$y' = Ay, \qquad y(0) = y_0$$

and the integrators

$$y_1 = y_0 + \Delta t A y_0,$$

$$y_1 = y_0 + \Delta t A y_0 + \frac{1}{2} \Delta t^2 A^2 y_0,$$

$$y_1 = y_0 + \Delta t A y_0 + c \Delta t^2 A^2 y_0.$$

Goal: design mixed-precision versions of these integrators preserving the original accuracy.

For $y_1 = y_0 + \Delta t A y_0 + c \Delta t^2 A^2 y_0$, $c \neq 1/2$:

Try 4:

For stability

$$\widehat{y}_1 = y_0 + \Delta t A y_0 + c \Delta t^2 \widehat{A^2 y_0}$$

$$= y_0 + \Delta t A y_0 + c \Delta t^2 A^2 y_0 + \mathcal{O}(\Delta t^2 u).$$

Local error: $\mathcal{O}(\Delta t^2 u)$.

Global error: $\mathcal{O}(\Delta tu)$.

Same order of convergence

Conclusion: harder to work with methods where coefficients are optimized for accuracy. But we can play with the stabilization terms.

Introduction to explicit stabilized methods



We want to solve, for instance,

$$y' = \nabla \cdot (A(y) \nabla y) + f(y).$$

We typically have:

Standard explicit solver: $\Delta t \leq Ch^2$,

Implicit solver: solves nonlinear problem.

With explicit stabilized methods:

- ullet No step size Δt restrictions,
- No linear systems to solve.

Some differences with respect to standard explicit methods:

- Adaptive in the number of stages s,
- Given an order p, use an increased number of stages $s \ge p$,
- Gained freedom is used to optimise in the stability direction,
- Stability domain grows as $O(s^2)$,
- Work load scales as $O(\sqrt{\rho}) = O(h^{-1})$, not as $O(\rho) = O(h^{-2})$.

The Runge-Kutta-Chebyshev method



Consider

$$y' = f(y),$$
 $y(0) = y_0.$

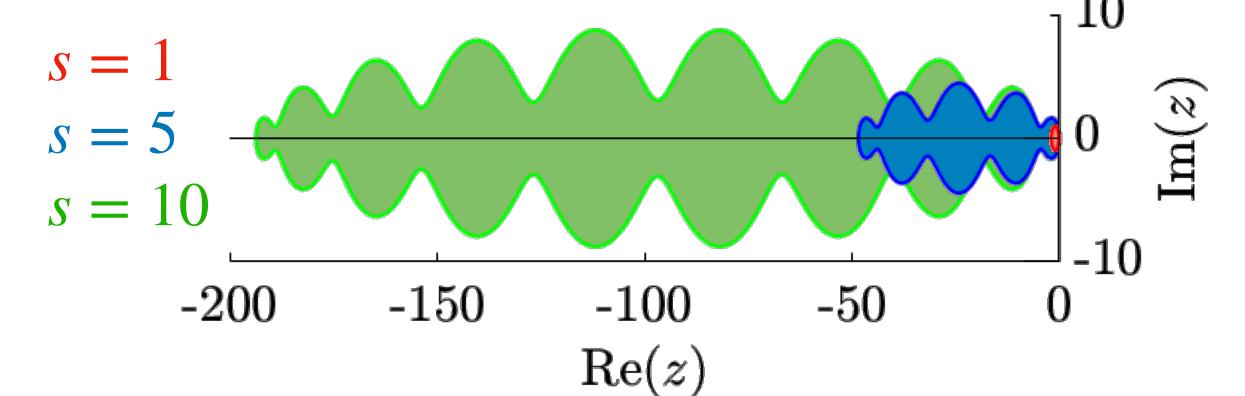
One step of RKC in δ -form is given by

$$d_0 = 0, d_1 = \mu_1 \Delta t f(y_0),$$

$$d_j = \nu_j d_{j-1} + \kappa_j d_{j-2} + \mu_j \Delta t f(y_0 + d_{j-1}), j = 2,..., s,$$

$$y_1 = y_0 + d_s,$$

with s satisfying $\Delta t \rho \leq 2s^2$.



- No step size restriction,
- Fully explicit,
- Straightforward to implement.

We note that the method needs:

- Only p = 1,2 function evaluations for accuracy,
- and s p for stability.

But every evaluation contributes to both, accuracy and stability! For a mixed-precision version, we need to refactor the method.

The Mixed-Precision Runge-Kutta-Chebyshev method



Original method:

$$d_{0} = 0, d_{1} = \mu_{1} \Delta t f(y_{0}),$$

$$d_{j} = \nu_{j} d_{j-1} + \kappa_{j} d_{j-2} + \mu_{j} \Delta t f(y_{0} + d_{j-1}), j = 2,...,s,$$

$$d_{j} = v_{j} d_{j-1} + \kappa_{j} d_{j-2} + \mu_{j} \Delta t \left(f(y_{0}) + \widehat{J(y_{0})} d_{j-1}\right)$$

$$y_{1} = y_{0} + d_{s},$$

$$d_{0} = 0, d_{1} = \mu_{1} \Delta t f(y_{0}),$$

$$d_{j} = \nu_{j} d_{j-1} + \kappa_{j} d_{j-2} + \mu_{j} \Delta t \left(f(y_{0}) + \widehat{J(y_{0})} d_{j-1}\right)$$

Linearized method:

$$d_0 = 0, d_1 = \mu_1 \Delta t f(y_0),$$

$$d_j = \nu_j d_{j-1} + \kappa_j d_{j-2} + \mu_j \Delta t \left(f(y_0) + J(y_0) d_{j-1} \right)$$

$$y_1 = y_0 + d_s,$$

Mixed-precision method:

$$d_0 = 0, d_1 = \mu_1 \Delta t f(y_0),$$

$$d_j = \nu_j d_{j-1} + \kappa_j d_{j-2} + \mu_j \Delta t \left(f(y_0) + \widehat{J(y_0)} d_{j-1} \right)$$

$$y_1 = y_0 + d_s,$$

 $J(y_0)d_{i-1}$ is computed with one low-precision evaluation of f.

Cost:

- 1 function evaluation in high-precision,
- s-1 function evaluation in low-precision.

Low-precision Jacobian's computation



The mixed-precision RKC method is:

$$d_0 = 0,$$
 $d_1 = \mu_1 \Delta t \, f(y_0),$ $d_j = \nu_j \, d_{j-1} + \kappa_j \, d_{j-2} + \mu_j \Delta t \, \left(f(y_0) + \widehat{J(y_0)} d_{j-1} \right)$

How do we approximate the Jacobian $\widehat{J(y_0)d_j}$ efficiently in low-precision?

Naive approach:

$$\widehat{J(y_0)d_j} := \widehat{f}(y_0 + d_j) - f(y_0) = f(y_0 + d_j) - f(y_0) + \mathcal{O}(u)$$

$$= J(y_0)d_j + \mathcal{O}(u + ||d_j||^2) = J(y_0)d_j + \mathcal{O}(u + \Delta t^2)$$

Local error: $\mathcal{O}(\Delta tu)$, Global error: $\mathcal{O}(u)$.

Low-precision Jacobian's computation



The mixed-precision RKC method is:

$$d_0 = 0,$$
 $d_1 = \mu_1 \Delta t f(y_0),$ $d_j = \nu_j d_{j-1} + \kappa_j d_{j-2} + \mu_j \Delta t \left(f(y_0) + \widehat{J(y_0)} d_{j-1} \right)$

How do we approximate the Jacobian $\widehat{J(y_0)d_j}$ efficiently in low-precision?

Smarter approach:

$$\widehat{J(y_0)d_j} := \epsilon^{-1} \left(\widehat{f}(y_0 + \epsilon d_j) - f(y_0) \right) = \epsilon^{-1} \left(f(y_0 + \epsilon d_j) - f(y_0) + \mathcal{O}(u) \right)$$

$$= \epsilon^{-1} \left(J(y_0)\epsilon d_j + \mathcal{O}(u + \epsilon^2 ||d_j||^2) \right) = J(y_0)d_j + \mathcal{O}(\epsilon^{-1}u + \epsilon\Delta t^2)$$

Take $\epsilon = \sqrt{u}/\Delta t$, then $\mathcal{O}(\epsilon^{-1}u + \epsilon \Delta t^2) = \mathcal{O}(\Delta t \sqrt{u})$.

Local error: $\mathcal{O}(\Delta t^2 \sqrt{u})$, Global error: $\mathcal{O}(\Delta t \sqrt{u})$.

Convergence and stability



Convergence

The global error between the high-precision and the mixed-precision RKC method is¹

$$\|y_n - \hat{y}_n\| = \mathcal{O}(\Delta t \sqrt{u})$$

 $\|y_n - \hat{y}_n\| = \mathcal{O}(\Delta t \sqrt{u})$ A second-order scheme exists, with

$$\|\mathbf{y}_n - \hat{\mathbf{y}}_n\| = \mathcal{O}(\Delta t^2)$$

Stability

- Roundoff errors destroy any spectral relationship between the error term and the solution,
- A stability analysis in the classical sense is undoable,
- The best that we can do is a worst-case analysis that doesn't take into account roundoff errors' cancellation¹,
- Numerical experiments show that our mixed-precision schemes are stable¹.

¹ M. Croci, G. Rosilho de Souza, Journal of Computational Physic, 464, 2022.

Stability Check



Solve

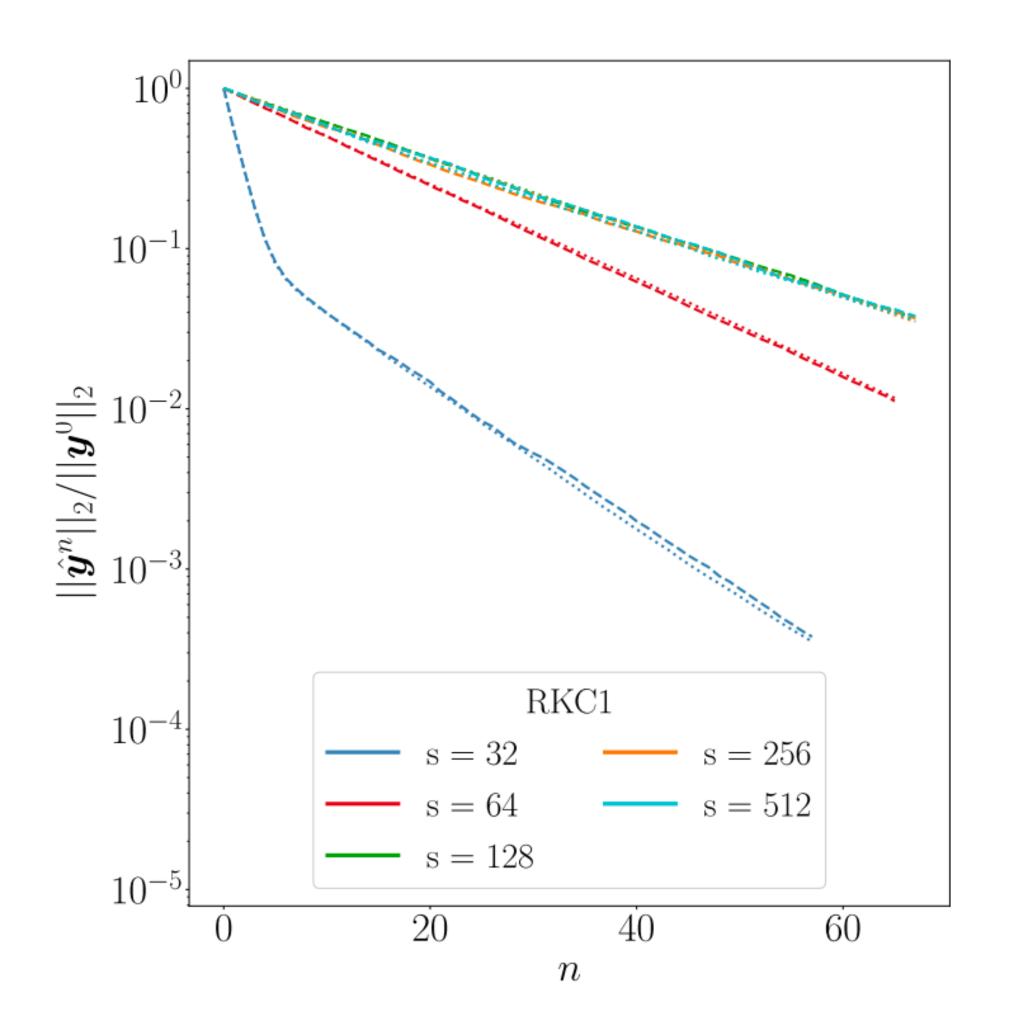
$$\frac{\partial u}{\partial t} = 100\Delta u \qquad \text{in } \Omega \times [0, T],$$

$$u(x, t) = 0 \qquad \text{on } \partial\Omega \times [0, T],$$

$$u(x, 0) = u_0(x) \qquad \text{in } \Omega,$$

with
$$\Omega = [0,1] \times [0,1]$$
, $T = 1$.

For different mesh sizes and fixed Δt , we check that the norm decreases in time.



Convergence experiment



Solve

$$\frac{\partial u}{\partial t} = \nabla \cdot (\|\nabla u\|_2^2 \nabla u) + f(x) \qquad \text{in } \Omega \times [0, T],$$

$$u(x, t) = 1 \qquad \qquad \text{on } \partial\Omega \times [0, T],$$

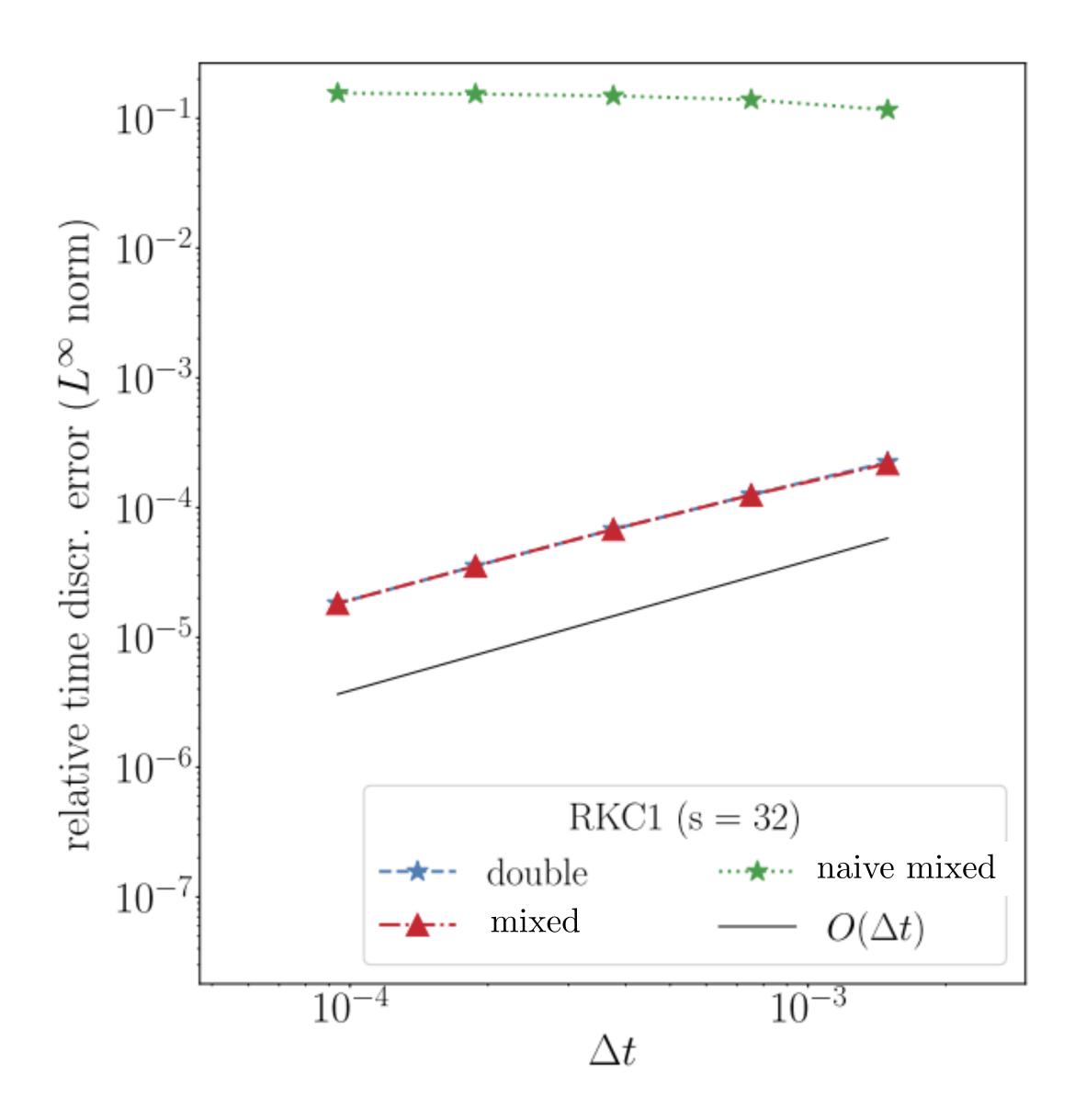
$$u(x, 0) = 1 \qquad \qquad \text{in } \Omega,$$

with
$$\Omega = [0,1], T = 1.$$

For h = 1/32 = 0.03125 and fixed s = 32 we let $\Delta t \to 0$ and plot the errors

$$\frac{1}{u} \|\hat{u}_n - u(t_n)\|_{L^{\infty}((0,T),L^{\infty}(\Omega))}$$

For both RKC1 and RKC2.



Convergence experiment



Solve

$$\frac{\partial u}{\partial t} = \nabla \cdot (\|\nabla u\|_2^2 \nabla u) + f(x) \quad \text{in } \Omega \times [0, T],$$

$$u(x, t) = 1 \quad \text{on } \partial\Omega \times [0, T],$$

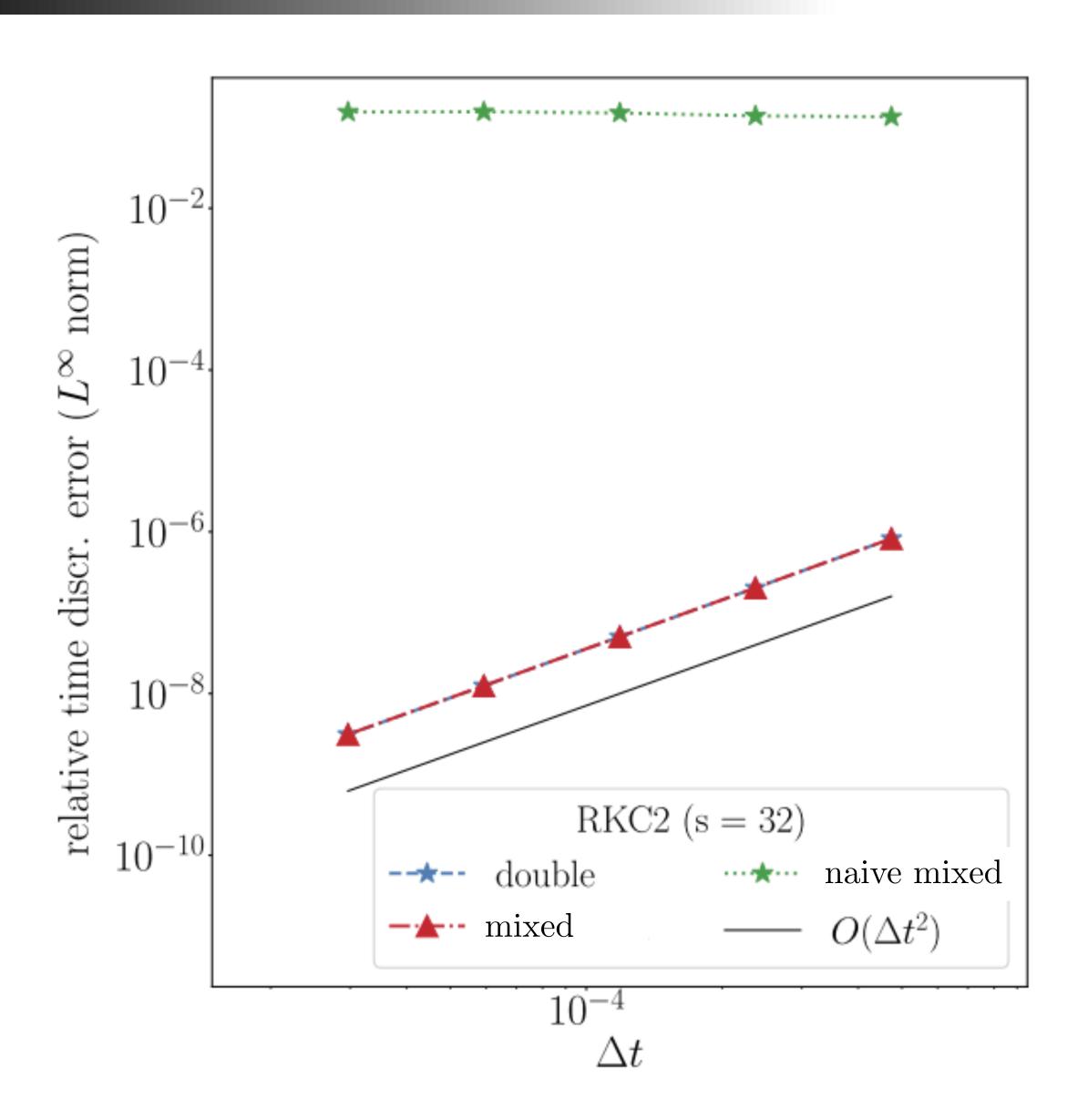
$$u(x, 0) = 1 \quad \text{in } \Omega,$$

with
$$\Omega = [0,1], T = 1.$$

For h = 1/32 = 0.03125 and fixed s = 32 we let $\Delta t \to 0$ and plot the errors

$$\frac{1}{u} \|\hat{u}_n - u(t_n)\|_{L^{\infty}((0,T),L^{\infty}(\Omega))}$$

For both RKC1 and RKC2.



Mixed precision multirate RKC method



Consider

$$y' = f_F(y) + f_S(y),$$
 $y(0) = y_0,$

with f_F stiff but cheap and f_S mildly stiff but expensive.

For RKC, number of expensive f_S evaluations is dictated by the few stiff terms in f_F and deteriorates efficiency.

We solve the modified problem

$$y'_{\eta} = f_{\eta}(y_{\eta}), \qquad y(0) = y_0,$$

With $\eta \ge 0$ a parameter used to tune the stiffness. For $\eta = 2/\rho_S$ the stiffness of f_{η} is same as f_S .

The averaged force is defined as

$$f_{\eta}(y) = \frac{1}{\eta} \left(u(\eta) - y \right)$$

With auxiliary solution u given by

$$u' = f_F(u) + f_S(y), u(0) = y.$$

The multirate RKC method is given by:

- Integrate $y'_{\eta} = f_{\eta}(y_{\eta})$ with a RKC method.
- To evaluate f_{η} solve $u' = f_F(u) + f_S(y)$ with another RKC method.

Mixed precision multirate RKC method



The multirate RKC method:

$$d_0 = 0, d_1 = \mu_1 \Delta t \, \bar{f}_{\eta}(y_0),$$

$$d_j = \nu_j \, d_{j-1} + \kappa_j \, d_{j-2} + \mu_j \Delta t \, \bar{f}_{\eta}(y_0 + d_{j-1}), \quad j = 2, \dots, s,$$

$$y_1 = y_0 + d_s,$$

With
$$\Delta t \rho_S \leq 2s^2$$
 and

$$h_0 = 0, h_1 = \alpha_1 (f_F(y) + f_S(y)),$$

$$h_j = \beta_j h_{j-1} + \gamma_j h_{j-2} + \alpha_j (f_F(y + \eta h_{j-1}) + f_S(y)),$$

$$\bar{f}_n(y) = h_m,$$

Where $\eta \rho_F \leq 2m^2$, $\eta \approx \Delta t/s^2$. Cost is:

- s evaluations of f_S in high-precision,
- $s \cdot m$ evaluations of f_F in high-precision.

The mixed-precision multirate RKC method:

$$\begin{split} d_0 &= 0, \qquad d_1 = \mu_1 \Delta t \; \hat{f}_{\eta}(y_0), \\ d_j &= \nu_j \; d_{j-1} + \kappa_j \; d_{j-2} + \mu_j \Delta t \left(\hat{f}_{\eta}(y_0) + \widehat{J_{\eta}(y_0)} d_{j-1} \right) \\ y_1 &= y_0 + d_s, \end{split}$$

- $\hat{f}_{\eta}(y_0)$ computed applying a mixed-precision RKC method to $\bar{f}_{\eta}(y)$.
- $J_{\eta}(y_0)d_{j-1}$ computed applying a low-precision RKC method to $\bar{f}_{\eta}(y)$.
- 1 evaluation of f_F , f_S in high-precision,
- Remaining evaluations in low-precision.

Numerical experiments



Solve

$$\frac{\partial u}{\partial t} = 100\Delta u + f_S(u, x) \quad \text{in } \Omega \times [0, T],$$

$$u(x, t) = 0 \quad \text{on } \partial\Omega \times [0, T],$$

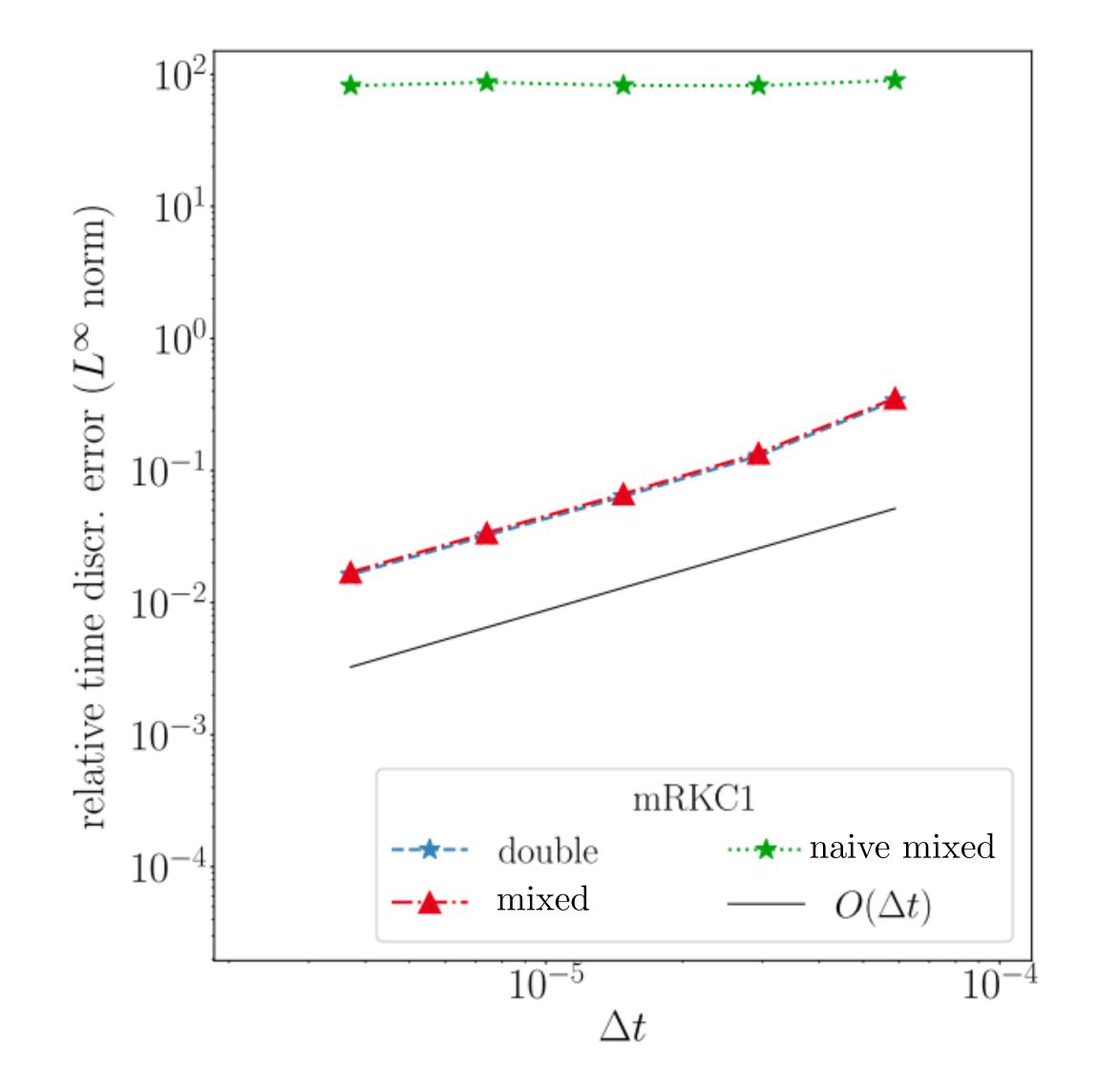
$$u(x, 0) = u_0(x) \quad \text{in } \Omega,$$

We fix mesh size h = 0.0156 and check convergence for $\Delta t \rightarrow 0$.

Plot errors

$$\frac{1}{u}\|\hat{u}_n - u(t_n)\| \text{ VS } \Delta t.$$

With fixed s = m = 10.



Numerical experiments

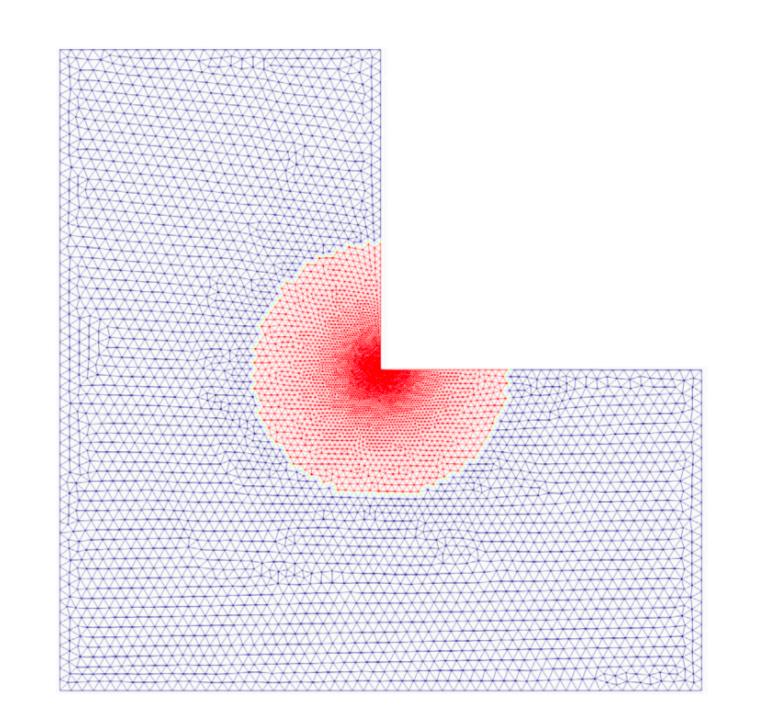


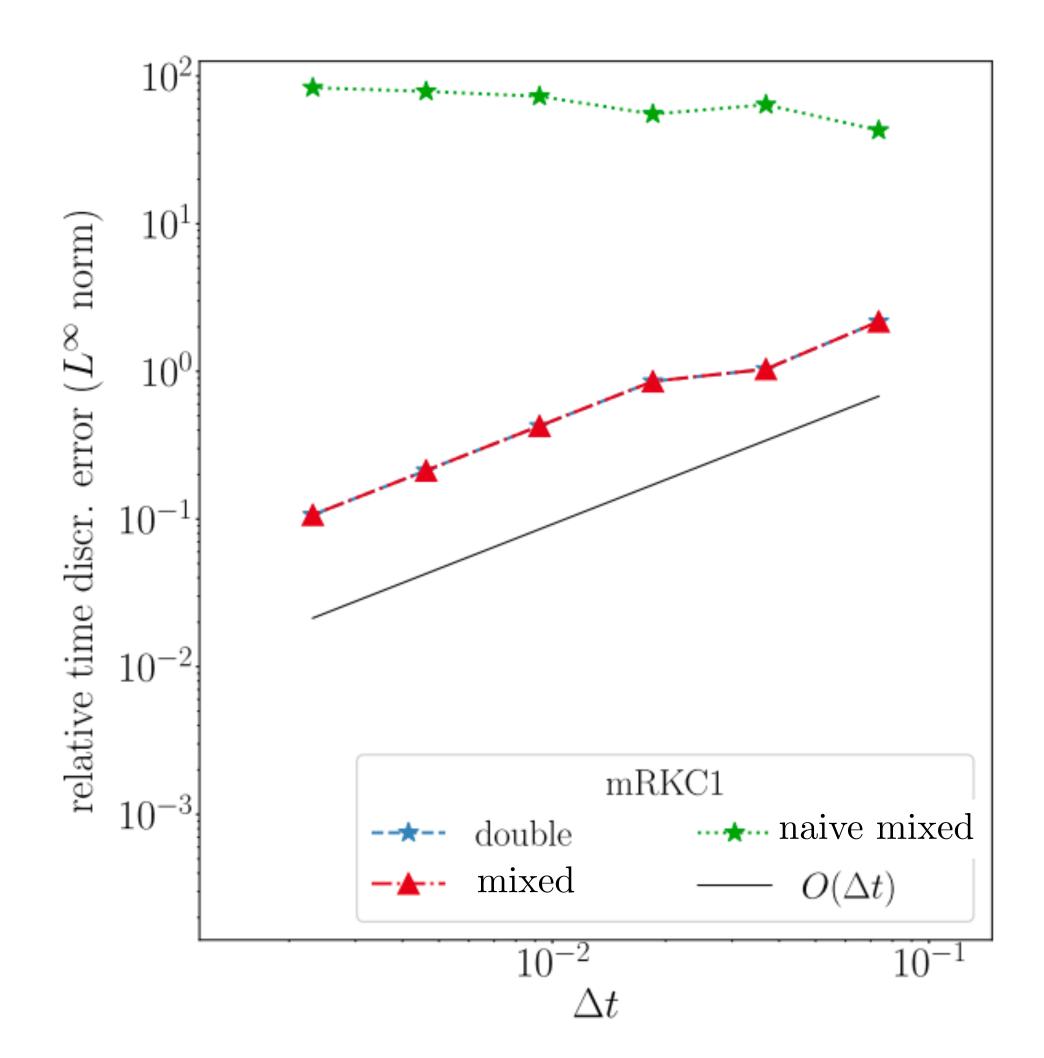
Solve

$$\frac{\partial u}{\partial t} = \Delta_F u + \Delta_S u + f_S(x) \quad \text{in } \Omega \times [0, T],$$

$$u(x, t) = 0 \quad \text{on } \partial\Omega \times [0, T],$$

$$u(x, 0) = u_0(x) \quad \text{in } \Omega,$$





Conclusions



Mixed-precision explicit stabilized methods for

$$y' = f(y)$$

- \bullet Only 1 high-precision evaluation of f,
- s-1 evaluations of f in low-precision, with $s=\mathcal{O}(\sqrt{\rho})$.
- Order 1 and 2 methods,
- Order of convergence is preserved (proved),
- Numerically stable.

Conclusions



Multirate mixed-precision explicit stabilized methods for

$$y' = f_F(y) + f_S(y)$$

- Only 1 high-precision evaluation of f_F , f_S ,
- s-1 evaluations of f_S in low-precision, with s depending on stiffness of f_S only: $s=\mathcal{O}(\sqrt{\rho_S})$.
- $s \cdot m 1$ evaluations of f_F in low-precision, with $s \cdot m = \mathcal{O}(\sqrt{\rho_F})$
- Order 1 method,
- Order of convergence is preserved (proved),
- Numerically stable.

Bibliography



Thank you!

■ Croci, M., & Rosilho de Souza, G. Mixed-precision explicit stabilized Runge-Kutta methods for single-and multi-scale differential equations. *Journal of Computational Physics*, 464, 2022.

Funding: This project has received funding from the Swiss National Science Foundation, under grant No. 200020_172710 and the European High-Performance Computing Joint Undertaking (JU) under grant agreement No 955701 (TIME-X). The JU receives support from the European Union's Horizon 2020 research and innovation programme and Belgium, France, Germany, and Switzerland.