

ADER and DeC: arbitrarily high order explicit time integration methods

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16th May 2020

joint work with Maria Han Veiga and Philipp Öffner

Outline

- 1 Motivation
- 2 DeC
- 3 ADER
- 4 Similarities
- 5 Simulations

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Motivation: high order accurate explicit method

We want to solve an ODE system for $\alpha : \mathbb{R}^+ \rightarrow \mathbb{R}^S$

$$\partial_t \alpha + F(\alpha) = 0. \quad (1)$$

Applications:

- Semidiscretized PDEs
- Chemical/biological processes

How?

- Arbitrarily high order accurate
-

Motivation: high order accurate explicit method

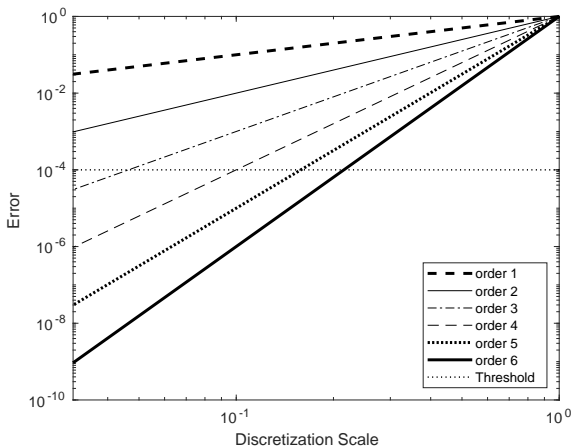
We want to

Application

- Semid
- Chemi

How?

- Arbitra
-



(1)

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How?

- Arbitrarily high order accurate
- Explicit

$$\boldsymbol{\alpha}^{(1)} := \boldsymbol{\alpha}^n, \quad (2)$$

$$\boldsymbol{\alpha}^{(k)} := \boldsymbol{\alpha}^n + \sum_{s=1}^K A_{ks} F\left(t^n + b_s \Delta t, \boldsymbol{\alpha}^{(s)}\right), \quad \text{for } k = 2, \dots, K, \quad (3)$$

$$\boldsymbol{\alpha}^{n+1} := \sum_{k=1}^K \gamma_k \boldsymbol{\alpha}^{(k)}. \quad (4)$$

$$\alpha^{(k)} := \alpha^n + \sum_{s=1}^{k-1} A_{ks} F \left(t^n + b_s \Delta t, \alpha^{(s)} \right), \quad \text{for } k = 2, \dots, K.$$

- Easy to solve
- High orders involved:
 - Order conditions: system of many equations
 - Stages $K \geq d$ order of accuracy (e.g. RK44, RK65)

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- More complicated to solve for nonlinear systems
- High orders easily done:
 - Take a high order quadrature rule on $[t^n, t^{n+1}]$
 - Compute the coefficients accordingly, see Gauss–Legendre or Gauss–Lobatto polynomials
 - Order up to $d = 2K - 1$

Two iterative explicit arbitrarily high order accurate methods.

- ADER¹ for hyperbolic PDE, after a first analytic more complicated approach.
- Deferred Correction (DeC): introduced for explicit ODE², extended to implicit ODE³ and to hyperbolic PDE⁴.

¹M. Dumbser, D. S. Balsara, E. F. Toro, and C.-D. Munz. A unified framework for the construction of one-step finite volume and discontinuous galerkin schemes on unstructured meshes. *Journal of Computational Physics*, 227(18):8209–8253, 2008.

²A. Dutt, L. Greengard, and V. Rokhlin. Spectral Deferred Correction Methods for Ordinary Differential Equations. *BIT Numerical Mathematics*, 40(2):241–266, 2000.

³M. L. Minion. Semi-implicit spectral deferred correction methods for ordinary differential equations. *Commun. Math. Sci.*, 1(3):471–500, 09 2003.

⁴R. Abgrall. High order schemes for hyperbolic problems using globally continuous approximation and avoiding mass matrices. *Journal of Scientific Computing*, 73(2):461–494, Dec 2017.

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Discretization of each time step $[t^n, t^{n+1}]$.

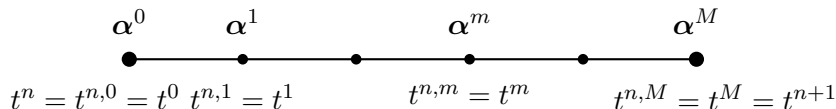


Figure: Subtime intervals

High order approximation of the equation in the Picard–Lindelöf form

$$\alpha^m = \alpha^0 - \int_{t^0}^{t^m} F(\alpha(t)) dt. \quad (5)$$

$$\begin{aligned}
\mathcal{L}^2(\boldsymbol{\alpha}^0, \dots, \boldsymbol{\alpha}^M) &= \begin{cases} \boldsymbol{\alpha}^M - \boldsymbol{\alpha}^0 - \int_{t^0}^{t^M} \mathcal{I}_M(F(\boldsymbol{\alpha}^0), \dots, F(\boldsymbol{\alpha}^M)) ds \\ \dots \\ \boldsymbol{\alpha}^1 - \boldsymbol{\alpha}^0 - \int_{t^0}^{t^1} \mathcal{I}_M(F(\boldsymbol{\alpha}^0), \dots, F(\boldsymbol{\alpha}^M)) ds \end{cases} \\
&= \begin{cases} \boldsymbol{\alpha}^M - \boldsymbol{\alpha}^0 - \sum_{r=0}^M \int_{t^0}^{t^M} F(\boldsymbol{\alpha}^r) \varphi_r(s) ds \\ \dots \\ \boldsymbol{\alpha}^1 - \boldsymbol{\alpha}^0 - \sum_{r=0}^M \int_{t^0}^{t^1} F(\boldsymbol{\alpha}^r) \varphi_r(s) ds \end{cases} \\
&= \begin{cases} \boldsymbol{\alpha}^M - \boldsymbol{\alpha}^0 - \Delta t \sum_{r=0}^M \theta_r^M F(\boldsymbol{\alpha}^r) \\ \dots \\ \boldsymbol{\alpha}^1 - \boldsymbol{\alpha}^0 - \Delta t \sum_{r=0}^M \theta_r^1 F(\boldsymbol{\alpha}^r) \end{cases}
\end{aligned}$$

Goal: find $\underline{\alpha}^* = (\alpha^0, \dots, \alpha^m, \dots, \alpha^M)^* : \mathcal{L}^2(\underline{\alpha}^*) = 0$.

- $\mathcal{L}^2 = 0$ is a system of $M \times S$ coupled (non)linear equations
- \mathcal{L}^2 is an implicit method
- Not easy to solve directly
- High order ($\geq M + 1$), depending on points distribution

$$\mathcal{L}^1(\boldsymbol{\alpha}^0, \dots, \boldsymbol{\alpha}^M) := \begin{cases} \boldsymbol{\alpha}^M - \boldsymbol{\alpha}^0 - \beta^M \Delta t F(\boldsymbol{\alpha}^0) \\ \vdots \\ \boldsymbol{\alpha}^1 - \boldsymbol{\alpha}^0 - \beta^1 \Delta t F(\boldsymbol{\alpha}^0) \end{cases} \quad \beta^m := \frac{t^m - t^0}{t^M - t^0}. \quad (6)$$

- First order approximation
- Explicit Euler
- Easy to solve $\mathcal{L}^1(\underline{\boldsymbol{\alpha}}) = 0$

K iterations where the iteration index is the superscript (k), with $k = 0, \dots, K$

- 1 Define $\alpha^{(0),m} = \alpha^n = \alpha(t^n)$ for $m = 0, \dots, M$
- 2 Define $\alpha^{(k),0} = \alpha(t^n)$ for $k = 0, \dots, K$
- 3 Find $\underline{\alpha}^{(k)}$ as $\mathcal{L}^1(\underline{\alpha}^{(k)}) = \mathcal{L}^1(\underline{\alpha}^{(k-1)}) - \mathcal{L}^2(\underline{\alpha}^{(k-1)})$
- 4 $\alpha^{n+1} = \alpha^{(K),M}$.

Theorem (Convergence DeC)

- If \mathcal{L}^1 coercive with constant C_1
- If $\mathcal{L}^1 - \mathcal{L}^2$ Lipschitz with constant $C_2\Delta t$

Then $\|\underline{\alpha}^{(k)} - \underline{\alpha}^*\| \leq C\Delta t^k$

Hence, choosing $K = M + 1$, then $\|\alpha^{(K),M} - \alpha^{ex}(t^{n+1})\| \leq C\Delta t^K$

Proof.

Let $\underline{\alpha}^*$ be the solution of $\mathcal{L}^2(\underline{\alpha}^*) = 0$. We know that $\mathcal{L}^1(\underline{\alpha}^*) = \mathcal{L}^1(\underline{\alpha}^*) - \mathcal{L}^2(\underline{\alpha}^*)$ and $\mathcal{L}^1(\underline{\alpha}^{(k+1)}) = (\mathcal{L}^1(\underline{\alpha}^{(k)}) - \mathcal{L}^2(\underline{\alpha}^{(k)}))$, so that

$$\begin{aligned} C_1 \|\underline{\alpha}^{(k+1)} - \underline{\alpha}^*\| &\leq \|\mathcal{L}^1(\underline{\alpha}^{(k+1)}) - \mathcal{L}^1(\underline{\alpha}^*)\| = \\ &= \|\mathcal{L}^1(\underline{\alpha}^{(k)}) - \mathcal{L}^2(\underline{\alpha}^{(k)}) - (\mathcal{L}^1(\underline{\alpha}^*) - \mathcal{L}^2(\underline{\alpha}^*))\| \leq \\ &\leq C_2 \Delta t \|\underline{\alpha}^{(k)} - \underline{\alpha}^*\|. \end{aligned}$$

$$\|\underline{\alpha}^{(k+1)} - \underline{\alpha}^*\| \leq \left(\frac{C_2}{C_1} \Delta t\right) \|\underline{\alpha}^{(k)} - \underline{\alpha}^*\| \leq \left(\frac{C_2}{C_1} \Delta t\right)^{k+1} \|\underline{\alpha}^{(0)} - \underline{\alpha}^*\|.$$

After K iteration we have an error at most of $\eta^K \cdot \|\underline{\alpha}^{(0)} - \underline{\alpha}^*\|$. □

DeC: Second order example

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Operators can be extended for space time discretization.

Example: PDEs, FEM discretization

The \mathcal{L}^2 operator contains also the complications of the spatial discretization (e.g. mass matrix)

The \mathcal{L}^1 operator can simplify everything up to a first order approximation (e.g. mass lumping)

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ADER: space-time discretization

Originally exploitation of Cauchy–Kovalevskaya theorem (many computations)

Modern approach is DG in space time for hyperbolic problem

$$\partial_t u(x, t) + \nabla \cdot F(u(x, t)) = 0, \quad x \in \Omega \subset \mathbb{R}^d, t > 0. \quad (7)$$

Defining $\theta_{rs}(x, t) = \Phi_r(x)\phi_s(t)$ basis functions in space and time

$$\int_{T^n \times V_i} \theta_{rs}(x, t) \partial_t \theta_{pq}(x, t) u^{pq} dx dt + \int_{T^n \times V_i} \theta_{rs}(x, t) \nabla \cdot F(\theta_{pq}(x, t) u^{pq}) dx dt = 0.$$

This leads to

$$\underline{\underline{M}}_{rspq} u^{pq} = \underline{\underline{r}}(\underline{\underline{u}})_{rs}, \quad (8)$$

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This leads to

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Simplify!

$$\int_{T^n} \psi(t) \partial_t \boldsymbol{\alpha}(t) dt + \int_{T^n} \psi(t) F(\boldsymbol{\alpha}(t)) dt = 0, \quad \forall \psi : T^n = [t^n, t^{n+1}] \rightarrow \mathbb{R}.$$

$$\mathcal{L}^2(\underline{\boldsymbol{\alpha}}) := \int_{T^n} \underline{\phi}(t) \partial_t \underline{\phi}(t)^T \underline{\boldsymbol{\alpha}} dt + \int_{T^n} \underline{\phi}(t) F(\underline{\phi}(t)^T \underline{\boldsymbol{\alpha}}) dt = 0$$

$$\underline{\phi}(t) = (\phi_0(t), \dots, \phi_M(t))^T$$

Quadrature...

$$\mathcal{L}^2(\underline{\boldsymbol{\alpha}}) := \underline{\underline{\mathbf{M}}}\underline{\boldsymbol{\alpha}} - \underline{r}(\underline{\boldsymbol{\alpha}}) = 0 \iff \underline{\underline{\mathbf{M}}}\underline{\boldsymbol{\alpha}} = \underline{r}(\underline{\boldsymbol{\alpha}}). \quad (9)$$

Nonlinear system of $M \times S$ equations

Iterative procedure to solve the problem for each time step

$$\underline{\alpha}^{(k)} = \underline{\underline{M}}^{-1} \underline{r}(\underline{\alpha}^{(k-1)}), \quad k = 1, \dots, \text{convergence} \quad (10)$$

with $\underline{\alpha}^{(0)} = \alpha(t^n)$.

- Convergence?
- How many steps K ?

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$$\begin{aligned}\mathcal{L}^2(\underline{\alpha}) &:= \underline{\underline{M}}\underline{\alpha} - r(\underline{\alpha}), \\ \mathcal{L}^1(\underline{\alpha}) &:= \underline{M}\underline{\alpha} - r(\underline{\alpha}(t^n)).\end{aligned}$$

$$\mathcal{L}^1(\underline{\alpha}^{(k)}) = \mathcal{L}^1(\underline{\alpha}^{(k-1)}) - \mathcal{L}^2(\underline{\alpha}^{(k-1)}), \quad k = 1, \dots, K,$$

defining $\alpha^{(k),0} = \alpha(t^n)$, $\forall k$. Hence, we can explicitly write it as

$$\underline{\underline{M}}\underline{\alpha}^{(k+1)} - r(\underline{\alpha}^{(k+1)}(t^n)) - \underline{\underline{M}}\underline{\alpha}^{(k)} + r(\underline{\alpha}^{(k)}(t^n)) + \underline{M}\underline{\alpha}^{(k)} - r(\underline{\alpha}^{(k)}) = 0$$

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Apply the DeC Convergence theorem!

- \mathcal{L}^1 is coercive because $\underline{\underline{M}}$ is always invertible
- $\mathcal{L}^1 - \mathcal{L}^2$ is Lipschitz with constant $C\Delta t$ because they are consistent approx of the same problem
- Hence, after K iterations we obtain a K th order accurate approximation of $\underline{\alpha}^*$

$$\mathcal{L}^2(\boldsymbol{\alpha}^0, \dots, \boldsymbol{\alpha}^M) := \begin{cases} \boldsymbol{\alpha}^M - \boldsymbol{\alpha}^0 - \int_{t^0}^{t^M} \mathcal{I}_M(F(\boldsymbol{\alpha}^0), \dots, F(\boldsymbol{\alpha}^M)) \\ \vdots \\ \boldsymbol{\alpha}^1 - \boldsymbol{\alpha}^0 - \int_{t^0}^{t^1} \mathcal{I}_M(F(\boldsymbol{\alpha}^0), \dots, F(\boldsymbol{\alpha}^M)) \\ \boldsymbol{\alpha}^M - \boldsymbol{\alpha}^0 - \sum_{r=0}^M \int_{t^0}^{t^M} F(\boldsymbol{\alpha}^r) \varphi_r(s) ds \\ \dots \\ \boldsymbol{\alpha}^1 - \boldsymbol{\alpha}^0 - \sum_{r=0}^M \int_{t^0}^{t^1} F(\boldsymbol{\alpha}^r) \varphi_r(s) ds \end{cases} .$$

and focus on the m -th line, which reads

$$\boldsymbol{\alpha}^m - \boldsymbol{\alpha}^0 - \sum_{r=0}^M F(\boldsymbol{\alpha}^r) \int_{t^0}^{t^m} \varphi_r(t) dt = 0.$$

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$$\chi_{[t^0, t^m]}(t^m) \boldsymbol{\alpha}^m - \chi_{[t^0, t^m]}(t^0) \boldsymbol{\alpha}^0 - \sum_{r=0}^M F(\boldsymbol{\alpha}^r) \int_{t^0}^{t^M} \chi_{[t^0, t^m]}(t) \varphi_r(t) dt = 0$$

$$\chi_{[t^0, t^m]}(t) = \begin{cases} 1, & \text{if } t \in [t^0, t^m], \\ 0, & \text{else.} \end{cases} \quad (11)$$

$$\int_{t^0}^{t^M} \chi_{[t^0, t^m]}(t) \partial_t (\boldsymbol{\alpha}(t)) dt - \sum_{r=0}^M F(\boldsymbol{\alpha}^r) \int_{t^0}^{t^M} \chi_{[t^0, t^m]}(t) \varphi_m(t) dt = 0,$$

$$\int_{T^n} \psi_m(t) \partial_t \boldsymbol{\alpha}(t) dt - \int_{T^n} \psi_m(t) F(\boldsymbol{\alpha}(t)) dt = 0.$$

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$$\int_{T^n} \psi_m(t) \partial_t \boldsymbol{\alpha}(t) dt - \int_{T^n} \psi_m(t) F(\boldsymbol{\alpha}(t)) dt = 0.$$

Both are

- Iterative processes (only iterations $K = d$ order of accuracy)
- Arbitrarily high order accurate
- Explicit

ADER as DeC iterative process

- The operators \mathcal{L}^1 and \mathcal{L}^2 can be written
- Convergence results hold
- We know in practice how many iteration K

DeC as ADER

- \mathcal{L}^2 is the same up to the choice of basis and test functions in time

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$$y'(t) = \lambda y(t) \quad (12)$$

$$y(0) = 1 \quad (13)$$

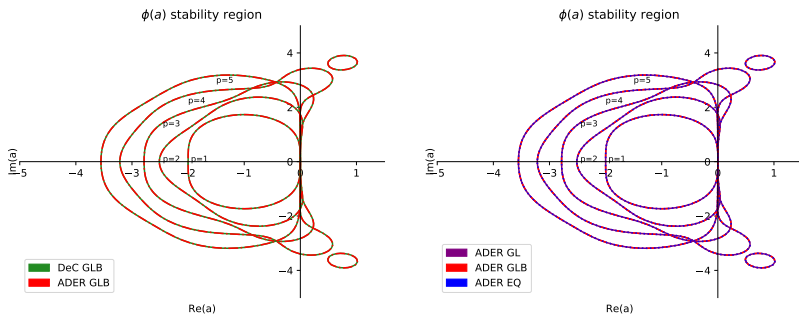
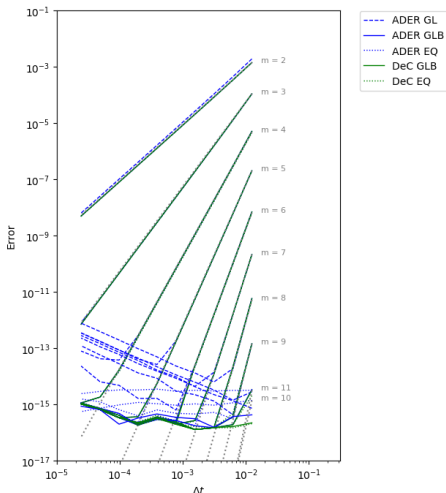


Figure: Stability region

Convergence

$$\begin{aligned}y'(t) &= -|y(t)|y(t), \\ y(0) &= 1, \\ t &\in [0, 0.1].\end{aligned}\quad (14)$$

Convergence curves for ADER and DeC, varying the approximation order and collocation of nodes for the subtimesteps for a scalar nonlinear ODE



Lotka–Volterra

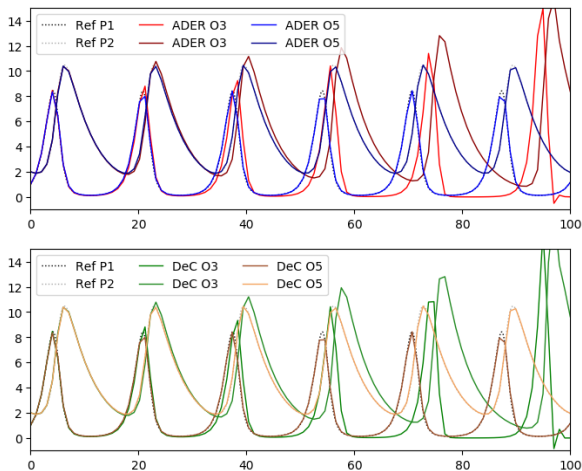


Figure: Numerical solution of the Lotka-Volterra system using ADER (top) and DeC (bottom) with Gauss-Lobatto nodes with timestep $\Delta T = 1$.

PDE: Burgers

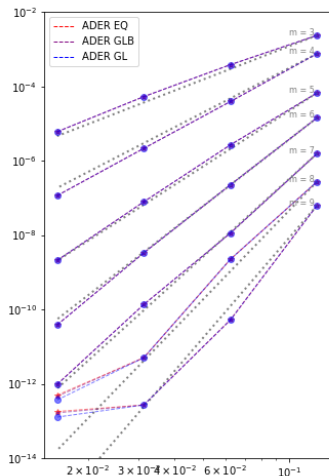


Figure: ADER

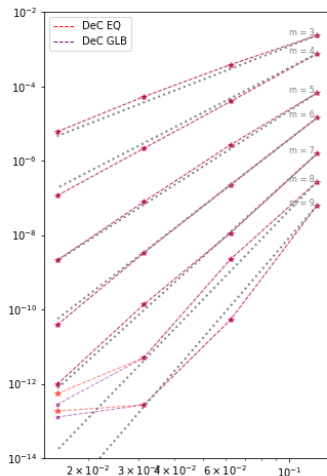


Figure: DeC

Thanks for the attention!
Questions?