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Novel adjoint advection schemes for Atmospheric Chemistry

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Outline

- *● Motivation*
	- *○ atmospheric chemistry & 4D-var data assimilation*

● Adjoint developments

● Numerical results

wind

Atmospheric chemistry transport modeling

General atmospheric processes

- **● emission**
- **● transport**
- **● chemistry**
- **● deposition**

Transport continuity equation

$$
\frac{\partial (\rho q)}{\partial t} + \nabla \cdot (\rho q v) = 0
$$

 ρ - density $-mass$ concnetration \boldsymbol{q} $v - wind$ velocity vector

Numerical models are used to simulate atmospheric motion and provide better understanding of the processes determining the dynamical and chemical state

Surface

Earth's

cold

Benefit from satellite observation data for improved

atmospheric chemistry and Climate Model performance

Combining models with observations: a complex mathematical optimisation task

ScienceBRIDGE

Result: the accuracy of the forecast is greatly improved

ICON Model

Joint project of German Weather Service (DWD) and Max-Plank Institute of Meteorology (MPI-M)

ICON model icosahedral grid, Zängl et. al, 2014

4D-var data assimilation (II)

Cost function

$$
J(q_0) = f^b(q_0, q^b) + \int_0^T \int_{\Omega} f^o(q, q^o, t, \lambda, \theta) d\lambda d\theta dt
$$

 Ω - surface of the sphere Source: ICON Database- Reference Manual (λ, θ) - longitude-latitude coordinates \vec{q}_0 - initial concentation (eg. greenhouse gases) \vec{q}° - observational data (satellite or ground-based measurements) \vec{q}^b - background information

Data assimilation problem: find the initial state q_0 that minimizes the cost function subject to the constraints:

$$
\frac{\partial(\rho q)}{\partial t} + \nabla \cdot (\rho q \vec{v}) = 0 \quad q(0, \lambda, \theta) = q_0(\lambda, \theta)
$$

Solution approach

Gradient

$$
\nabla_{q_0} J(q_0) = \nabla_{q_0} f^b(q_0, q^b) - \rho(0, \lambda, \theta) q^*(0, \lambda, \theta)
$$

 $q^*(0, \lambda, \theta)$ -solution at $t = 0$ of the adjoint equation

Adjoint equation

$$
\rho(\frac{\partial q^*}{\partial t} + v \cdot \nabla q^*) = \nabla_q f^o(q, q^o, t, \lambda, \theta), \quad q^*(T, \lambda, \theta) = 0
$$

Numerical challenge for adjoint development

- Delta-peak like transport during backward transport of $\nabla_a f^{\circ}(q, q^o, t, \lambda, \theta)$ requires **non-linear schemes**
- **MPI based parallel computations**
- Long time needed on adjoint development and verification

Paths to build the adjoint code

Standard method

Paths to build the adjoint code

Adjoint operators for ICON advection schemes

Splitted 3D continuity equation

ICON Schemes

- Miura's scheme with third order least square reconstruction **Adjoint for horizontal** scheme
- Third order Piecewise
 Adjoint for vertical scheme Parabolic Method (PPM)

FCT Zalesak limiter (1979)

ICON-FFSL and its adjoint: standard method

● Forward scheme

 $\frac{\rho_j^{n+1}q_j^{n+1} - \rho_j^n q_j^n}{\Delta t} + \frac{1}{|\Omega_j|} \sum_{i \in S_j} \alpha_{ji} (\{\bar{\rho}_k^n, \bar{v}_k^n\}_{k \in K_{ji}}) q_i^n = 0, \ \ S_j = \bigcup_{i \in I_j} K_{ji}$

● Adjoint scheme

$$
\bar{\rho}_j^n \frac{q_j^{*,n+1} - q_j^{*,n}}{\Delta t} + \frac{1}{|\Omega_j|} \sum_{i \in S_j^*} \alpha_{ij} (\{\bar{\rho}_k^n, \bar{v}_k^n\}_{k \in K_{ij}}) q_i^{*,n} = 0
$$

 K_{ji} -reference number of cells for flux F_{ji} -reference number of cells on the stencil $\,$ S_i $I_j = \{1, 2, 3\}$

New method: artificial source term adjoint (I)

New method: artificial source term adjoint (II)

Theory:

- **● If forward scheme is stable adjoint scheme is also stable**
- **● If accuracy of forward scheme is O(h^k) then accuracy of adjoint scheme is O(h^k)**
- **● If forward scheme is convergent then adjoint scheme is also convergent for smooth solution**

ICON-FFSL and its adjoint: art. source term method

$$
\rho \frac{\partial q^*}{\partial t} + \nabla \cdot (\rho q^* \vec{v}) = q^* \nabla \cdot (\rho \vec{v})
$$

$$
\bar{\rho}_j^n \frac{q_j^{*,n+1} - q_j^{*,n}}{\Delta t} + \frac{1}{|\Omega_j|} \sum_{i \in I_j} F_{ji}(\{\bar{\rho}_j^n, \bar{v}_k^n, q_k^{*,n}\}_{k \in K_{ji}}, \vec{n}_{ji}, l_{ji}) =
$$

$$
\frac{1}{|\Omega_j|} \sum_{i \in I_j} F_{ji}(\{\bar{\rho}_j^n, \bar{v}_k^n, q_j^{*,n}\}_{k \in K_{ji}}, \vec{n}_{ji}, l_{ji})
$$

Using new method, limiters are directly inherited in adjoint equation, while for standard adjoint numerical scheme development extra procedure is necessary to include limiters.

Numerical experiments - do the methods work ? ● Linear horizontal advection

- Divergent velocity
- Non-divergent velocity
- **FCT Zalesak Flux limiter** (1979)
- One full rotation-12 days

Error norms

$$
l_{1,rel} = \frac{\sum_{i=1}^{n_c} |\Omega_i| |q_i - q_i^{true}|}{\sum_{i=1}^{n_c} |\Omega_i| |q_i^{true}|}
$$

\n
$$
l_{2,rel} = \frac{\sqrt{\sum_{i=1}^{n_c} |\Omega_i| |q_i^{true}|}}{\sqrt{\sum_{i=1}^{n_c} |\Omega_i| |q_i^{true}|}}
$$

\n
$$
l_{\infty,rel} = \frac{\max_{i=1, n_c} |q_i - q_i^{true}|}{\max_{i=1, n_c} |q_i^{true}|}
$$

\n
$$
l_{1,abs} = \sum_{i=1}^{n_c} |q_i - q_i^{true}|
$$

\n
$$
l_{2,abs} = \sqrt{\sum_{i=1}^{n_c} (q_i - q_i^{true})^2}
$$

\n
$$
l_{\infty,abs} = \max_{i=1, n_c} |q_i - q_i^{true}|
$$

Results: linear advection (I)

● Standard adjoint method introduces oscillations and might leads to

negative concentration

 1.2

 $\mathbf{1}$

 0.8

0.6

 0.4

 0.2

 $\overline{0}$

 2π

Results: linear advection (II)

● Artificial source term method has better shape precervance, smaller

error norms

Numerical experiments

● Data assimilation

- Convergence
- Impact of observation points
- Mesh refinement
- Manipulating with weights
- Deformational flow with non-divergent velocity vector
- Moving vortex
- ➢*Identical twin experiment*
- ➢*12 hr assimilation window*
- ➢*Grids: R2B4, R2B5, R2B6, R2B7*
- ➢*Observations: 12.5%, 25%, 50%, 100%*
- ➢*Initial error: 10%, or 1% if concentration=0*
- ➢*Observation at each time-step*

Results: data assimilation (I)

● Convergence

Both methods ensure convergence with increasing number of iterations

The choice of adjoint solver influences the minimisation process

Number of observations b Impact of number of observations

Artificial source term method offers more reliable behavior in most cases

 $C_{\alpha\alpha}$ +

 Λ \rightarrow +

 $\bigcap_{n=1}^{\infty}$

Mesh refinement

course odicint

 A_{m+1}

● Mesh refinement

Art. source term method yelds smaller final cost function

● Manipulating with weights The choice of adjoint solver influences the minimisation process

Manipulating with weights

Artificial source term method gives good results when standard approach fails

3D pure tracer advection test (Jablonowski, 2008)

Horizontal velocity vector $u(\lambda, \theta, \eta) = u_0 \cos(\theta \cos \alpha + \sin \theta \cos \lambda \sin \alpha),$ $v(\lambda, \theta, \eta) = -u_0 \sin \lambda \sin \alpha$

● Vertical velocity vector

$$
\dot{\eta}(\lambda,\theta,\eta) = \frac{\omega_0}{p_0} \cos(\frac{2\pi}{\tau}t) \sin(s(\eta)\frac{\pi}{2})
$$

- Solid body rotation in horizontal direction with a period of 12 days
- Wave-like trajectory in the vertical direction with a period of 4 days
- ➢ 60 vertical layers up to ≈12 km.

Data assimilation results

➢ *Initial error: 10%, or 1% if concentration=0, on the layers 34-42* ➢*Observation at each time-step*

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