

Aerothermodynamic Design Sensitivities for a Reacting Gas Flow Solver on an Unstructured Mesh Using a Discrete Adjoint Formulation

Kyle B. Thompson

Mechanical and Aerospace Engineering Department
North Carolina State University

Aerothermodynamics Branch
NASA Langley Research Center

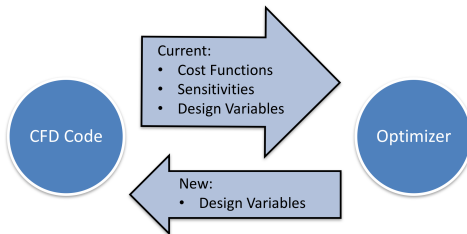
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Outline

- 1 Introduction
- 2 Flow Solver
 - Fully-Coupled Flow Solver
 - Decoupled Flow Solver
 - Cost and Memory Savings of the Decoupled Flow Solver
- 3 Adjoint Solver
 - Derivation of Discrete Adjoint Formulation
 - Fully Coupled Adjoint Solver
 - Decoupled Adjoint Method

Introduction - Design

- Gradient-based design optimization is based on the minimization of a target “cost” function by changing a set of design variables
- A CFD code can be coupled with a numerical optimization package to iteratively improve target aerothermodynamic quantities, by change inputs to the CFD code



CFD-Optimizer Relationship

Introduction - Design

- The top-level design process is simple, but CFD sensitivity analysis is expensive

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- Need efficient way to compute cost function sensitivities for large number of design variables

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Direct differentiation approach - Expensive

- Navier-Stokes equations can be directly differentiated to yield sensitivity derivatives necessary for gradient-based optimization
- Finite difference requires a minimum of **one flow solution for each design variable sensitivity**
- Prohibitively expensive for large number of design variables

Introduction - Design

- The top-level design process is simple, but CFD sensitivity analysis is expensive
- Need efficient way to compute cost function sensitivities for large number of design variables

Adjoint approach - More efficient

- Solve adjoint equations in addition to Navier Stokes flow equations to obtain sensitivity derivatives
- **One flow and adjoint solution needed for each cost function**, regardless of number of design variables
- Considerably more efficient than direct differentiation approach for large number of design variables

Introduction - Design

- Adjoint-based design optimization is widely adopted in compressible, perfect gas CFD solvers
- Reacting flow solvers have lagged in adopting adjoint-based approach, due to
 - ① Complexity of linearizing the additional equations for multi-species chemical kinetics
 - ② Resorting to Automatic Differentiation tools incurs performance overhead that is implementation-specific
 - ③ Serious memory and computational cost concerns when simulating a large number of species
- Points 1 and 2 can be overcome through stubbornness (or hiring a graduate student. . .)
- Point 3 is a serious concern, if reacting flow solvers are to be made attractive for design optimization

Introduction - Improvement to State of the Art

- Current state of the art
 - Attempts made at both continuous¹ and discrete² adjoint formulations for a compressible reacting flow solver
 - These attempts suffer from quadratic scaling in memory and computational cost with number of species
 - Recent scheme at Barcelona Supercomputing Center³ is promising, but only for incompressible reacting flows
- Improvement to the state of the art
 - New decoupled scheme for both hypersonic flow solver and adjoint solver that is robust for high-speed flows in chemical non-equilibrium
 - New schemes significantly improve scaling in computational cost and memory with number of species

¹Copeland.

²Lockwood.

³Esfahani:2016aa.

Introduction - Decoupled Approach

- Reacting gas simulations require solving a large number of conservation equations
- Memory concerns
 - Size of Jacobians scales quadratically with number species in gas mixture
 - Solving system of equations in a tightly-coupled fashion can be limited by memory constraints
- Cost concerns
 - Cost of solving the linear system scales quadratically with number of species in gas mixture
- Efficiently solving adjoint problem is a primary motivator
 - Solving adjoint system particularly costly if linear solver is slow
 - Can be necessary to store jacobian twice → large memory overhead

Introduction - Decoupled Approach

- Loosely-coupled solvers have become popular in the combustion community⁴
 - Decouple species conservation equations from meanflow equations, and solve two smaller systems

$$\begin{pmatrix} \square & \square & \dots & \square \\ \square & \square & \dots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \square & \dots & \dots & \square \end{pmatrix} \rightarrow \begin{pmatrix} \square & \dots & \square \\ \vdots & \ddots & \vdots \\ \square & \dots & \square \end{pmatrix}_{5 \times 5} \text{ and } \begin{pmatrix} \square & \boxtimes & \dots & \boxtimes \\ \boxtimes & \square & \dots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \boxtimes & \dots & \dots & \square \end{pmatrix}_{ns \times ns}$$

- Candler, et al.⁵ originally derived this for Steger-Warming scheme, this work extends to Roe FDS scheme

⁴Sankaran.

⁵candler.

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Fully-Coupled Point Implicit Flow Solver

- All work presented is for inviscid flows in chemical non-equilibrium, using a one-temperature model, but is extendable to viscous flows.
- Beginning with the semi-discrete form

$$\frac{\partial \mathbf{U}}{\partial t} + \frac{1}{V} \sum_f (\mathbf{F} \cdot \mathbf{S})^f = \mathbf{W}$$

$$\mathbf{U} = \begin{pmatrix} \rho_1 \\ \vdots \\ \rho_{ns} \\ \rho u \\ \rho v \\ \rho w \\ \rho E \end{pmatrix}, \quad \mathbf{F} \cdot \mathbf{S} = \begin{pmatrix} \rho_1 \bar{U} \\ \vdots \\ \rho_{ns} \bar{U} \\ \rho u \bar{U} + p s_x \\ \rho u \bar{U} + p s_y \\ \rho u \bar{U} + p s_z \\ (\rho E + p) \bar{U} \end{pmatrix} S, \quad \mathbf{W} = \begin{pmatrix} \dot{\rho}_1 \\ \vdots \\ \dot{\rho}_{ns} \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

Fully-Coupled Point Implicit Flow Solver

- Using the Roe FDS scheme to compute the inviscid flux at the face, \mathbf{F}^f , and linearizing the system results in

$$\begin{aligned}\frac{\delta \mathbf{U}^n}{\Delta t} + \frac{1}{V} \sum_f \left(\frac{\partial \mathbf{F}^f}{\partial \mathbf{U}^L} \delta \mathbf{U}^L + \frac{\partial \mathbf{F}^f}{\partial \mathbf{U}^R} \delta \mathbf{U}^R \right)^n \mathbf{S}^f - \frac{\partial \mathbf{W}}{\partial \mathbf{U}} \delta \mathbf{U}^n \\ = -\frac{1}{V} \sum_f (\mathbf{F}^f \cdot \mathbf{S}^f)^n + \mathbf{W}^n\end{aligned}$$

- Which can be thought of more simply as

$$\mathbf{A} \mathbf{u} = \mathbf{b}$$

$$\mathbf{A} \rightarrow \begin{array}{l} (4 + ns) \times (4 + ns) \\ \text{Jacobian Block} \end{array}$$

$$\mathbf{b} \rightarrow \begin{array}{l} (4 + ns) \times 1 \\ \text{Residual} \end{array}$$

Fully-Coupled Point Implicit Flow Solver

- Constructing the Jacobian in a fully-coupled fashion results in large, dense block matrices
- Using a stationary iterative method (i.e., Gauss-Seidel, SSOR, etc.), work is dominated by matrix-vector products

$$\text{Cost} \rightarrow O((4 + ns)^2)$$

- Leads to onerous quadratic scaling with respect to number of species

Decoupled Point Implicit Flow Solver

- The main idea is to separate the meanflow and species composition equations, adding a new equation for the total mixture density
- Leads to two sets of conserved variables

$$\mathbf{U}' = \begin{pmatrix} \rho \\ \rho u \\ \rho v \\ \rho w \\ \rho E \end{pmatrix} \quad \hat{\mathbf{U}} = \begin{pmatrix} \rho_1 \\ \vdots \\ \rho_{ns} \end{pmatrix}$$

Meanflow

Species Composition

Decoupled Point Implicit Flow Solver

- The fluxes are solved in two sequential steps
 - The mixture fluxes are first solved as

$$\frac{\partial \mathbf{U}'}{\partial t} + \frac{1}{V} \sum_f (\mathbf{F}' \cdot \mathbf{S})^f = 0$$

- Followed by the species fluxes

$$\frac{\partial \hat{\mathbf{U}}}{\partial t} + \frac{1}{V} \sum_f (\hat{\mathbf{F}} \cdot \mathbf{S})^f = \hat{\mathbf{W}}$$

- Since the mixture density was determined in the first step, step two actually solves for the species mass fractions

$$\delta \hat{\mathbf{U}}^n = \rho^{n+1} \hat{\mathbf{V}}^{n+1} - \rho^n \hat{\mathbf{V}}^n = \rho^{n+1} \delta \hat{\mathbf{V}}^n + \hat{\mathbf{V}}^n \delta \rho^n$$

$$\hat{\mathbf{V}} = (c_1, \dots, c_{ns})^T, c_s = \rho_s / \rho$$

Decoupled Point Implicit Flow Solver

- The Roe FDS scheme species mass fluxes can be rewritten as

$$\begin{aligned}\hat{\mathbf{F}}_{\rho_s} &= c_s \mathbf{F}'_{\rho} + (c_s^L - \tilde{c}_s) \rho^L \lambda^+ + (c_s^R - \tilde{c}_s) \rho^R \lambda^- \\ \frac{\partial \hat{\mathbf{F}}_{\rho_s}}{\partial c_s^L} &= w \mathbf{F}_{\rho} + (1 - w) \rho^L \lambda^+ - w \rho^R \lambda^- \\ \frac{\partial \hat{\mathbf{F}}_{\rho_s}}{\partial c_s^R} &= (1 - w) \mathbf{F}_{\rho} + (w - 1) \rho^L \lambda^+ + w \rho^R \lambda^-\end{aligned}$$

- Jacobian Approximations

$$\text{Step 1: } \left. \frac{\partial \mathbf{F}}{\partial \mathbf{U}'} \right|_{\hat{\mathbf{V}}} = 5 \times 5 \text{ Roe FDS Jacobian}_{c_s = \text{Constant}}$$

$$\text{Step 2: } \left. \frac{\partial \mathbf{F}}{\partial \hat{\mathbf{V}}} \right|_{\hat{\mathbf{U}}'} = \begin{pmatrix} \frac{\partial F_{\rho_1}}{\partial c_1} & & 0 \\ & \ddots & \\ 0 & & \frac{\partial F_{\rho_{ns}}}{\partial c_{ns}} \end{pmatrix}$$

Decoupled Point Implicit Flow Solver

- Chemical source term linearized via

$$\hat{\mathbf{W}}^{n+1} = \hat{\mathbf{W}}^n + \left. \frac{\partial \hat{\mathbf{W}}}{\partial \mathbf{U}} \right|_{\mathbf{U}'} \frac{\partial \mathbf{U}}{\partial \hat{\mathbf{V}}}$$

$$\mathbf{C} = \left. \frac{\partial \hat{\mathbf{W}}}{\partial \mathbf{U}} \right|_{\mathbf{U}'} \frac{\partial \mathbf{U}}{\partial \hat{\mathbf{V}}}$$

- Full system to be solved in step two

$$\begin{aligned} \rho^{n+1} \frac{\delta \hat{\mathbf{V}}^n}{\Delta t} + \frac{1}{V} \sum_f \left(\frac{\partial \hat{\mathbf{F}}^f}{\partial \mathbf{V}^L} \delta \mathbf{V}^L + \frac{\partial \hat{\mathbf{F}}^f}{\partial \hat{\mathbf{V}}^R} \delta \hat{\mathbf{V}}^R \right)^{n,n+1} \mathbf{S}^f - \mathbf{C}^{n,n+1} \delta \mathbf{V}^n \\ = -\frac{1}{V} \sum_f (\hat{\mathbf{F}}^{n,n+1} \cdot \mathbf{S})^f + \mathbf{W}^{n,n+1} - \hat{\mathbf{V}}^n \left(\frac{\delta \rho^n}{\Delta t} - R_\rho \right) \\ R_\rho = -\frac{1}{V} \sum_f \sum_s (\hat{F}_{\rho_s}^{n,n+1} \cdot \mathbf{S}) \end{aligned}$$

- R_ρ is included to preserve $\sum_s c_s = 1$, $\sum_s \delta c_s = 0$.

Cost and Memory Savings of the Decoupled Flow Solver

- Most significant savings comes from the source term linearization being purely node-based
 - Convective contributions to block Jacobians are diagonal
 - Source term jacobian is dense block Jacobian
 - In the global system (w/chemistry), all off-diagonal block jacobians are diagonal

$$\begin{pmatrix} \square & & & \\ & \ddots & & \\ & & \square & \\ & & & \ddots \\ & & & & \square \end{pmatrix} \begin{pmatrix} \delta \hat{\mathbf{V}}_1 \\ \vdots \\ \delta \hat{\mathbf{V}}_i \\ \vdots \\ \delta \hat{\mathbf{V}}_{nodes} \end{pmatrix} = \begin{pmatrix} \hat{b}_1 \\ \vdots \\ \hat{b}_i \\ \vdots \\ \hat{b}_{nodes} \end{pmatrix} - \begin{pmatrix} (\sum_{j=1}^{N_{nb}} [\mathcal{N}] \delta \hat{\mathbf{V}}_j)_1 \\ \vdots \\ (\sum_{j=1}^{N_{nb}} [\mathcal{N}] \delta \hat{\mathbf{V}}_j)_i \\ \vdots \\ (\sum_{j=1}^{N_{nb}} [\mathcal{N}] \delta \hat{\mathbf{V}}_j)_{nodes} \end{pmatrix}$$

- Matrix-vector products \rightarrow inner products: $O(ns^2) \rightarrow O(ns)$

Cost and Memory Savings of the Decoupled Flow Solver

- Comparing size of Jacobian systems, using Compressed Row Storage

\mathbf{A}_d = Decoupled system Jacobians

\mathbf{A} = Fully-coupled system Jacobians

$$\begin{aligned} \text{Relative Memory Cost} &= \frac{\text{size}(\mathbf{A}_d)}{\text{size}(\mathbf{A})} \\ &= \lim_{ns \rightarrow \infty} \frac{(ns^2 + 5^2)(N_{nodes}) + (ns + 5^2)(N_{nbrs})}{(ns + 4)^2(N_{nodes} + N_{nbrs})} \\ &= \frac{N_{nodes}}{N_{nodes} + N_{nbrs}} \end{aligned}$$

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Derivation of Discrete Adjoint Formulation

- The derivation of the adjoint approach to compute design sensitivities begins with forming the Lagrangian and differentiating with respect to the design variables

$$L(\mathbf{D}, \mathbf{Q}, \mathbf{X}, \boldsymbol{\Lambda}) = f(\mathbf{D}, \mathbf{Q}, \mathbf{X}) + \boldsymbol{\Lambda}^T \mathbf{R}(\mathbf{D}, \mathbf{Q}, \mathbf{X})$$

D = design variables

f = cost function

Q = flow variables

R = flow residual

X = computational grid

$\boldsymbol{\Lambda}$ = costate variables

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$$\begin{aligned} \frac{\partial L}{\partial \mathbf{D}} = & \left\{ \frac{\partial f}{\partial \mathbf{D}} + \left[\frac{\partial \mathbf{X}}{\partial \mathbf{D}} \right]^T \frac{\partial f}{\partial \mathbf{X}} \right\} + \left[\frac{\partial \mathbf{Q}}{\partial \mathbf{D}} \right]^T \left\{ \frac{\partial f}{\partial \mathbf{Q}} + \left[\frac{\partial \mathbf{R}}{\partial \mathbf{Q}} \right]^T \boldsymbol{\Lambda} \right\} \\ & + \left\{ \left[\frac{\partial \mathbf{R}}{\partial \mathbf{D}} \right]^T + \left[\frac{\partial \mathbf{X}}{\partial \mathbf{D}} \right]^T \left[\frac{\partial \mathbf{R}}{\partial \mathbf{X}} \right]^T \right\} \boldsymbol{\Lambda} \end{aligned}$$

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\mathbf{D} = design variables

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Derivation of Discrete Adjoint Formulation

- Need to eliminate flow variable dependence on design variables, $\frac{\partial \mathbf{Q}}{\partial \mathbf{D}}$
- Adjoint equation

$$\left[\frac{\partial \mathbf{R}}{\partial \mathbf{Q}} \right]^T \Lambda = - \frac{\partial f}{\partial \mathbf{Q}}$$

- Solve for Λ and compute sensitivity derivatives

$$\frac{\partial L}{\partial \mathbf{D}} = \left\{ \frac{\partial f}{\partial \mathbf{D}} + \left[\frac{\partial \mathbf{X}}{\partial \mathbf{D}} \right]^T \frac{\partial f}{\partial \mathbf{X}} \right\} + \left\{ \left[\frac{\partial \mathbf{R}}{\partial \mathbf{D}} \right]^T + \left[\frac{\partial \mathbf{X}}{\partial \mathbf{D}} \right]^T \left[\frac{\partial \mathbf{R}}{\partial \mathbf{X}} \right]^T \right\} \Lambda$$

Fully Coupled Adjoint Solver

- Adjoint problem is a linear system

$$\begin{pmatrix} \frac{\partial \mathbf{R}_{\rho i}}{\partial \rho_j}^T & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho_j}^T & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho_j}^T \\ \frac{\partial \mathbf{R}_{\rho i}}{\partial \rho u}^T & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho u}^T & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho u}^T \\ \frac{\partial \mathbf{R}_{\rho i}}{\partial \rho E}^T & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho E}^T & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho E}^T \end{pmatrix} \begin{pmatrix} \Lambda_{\rho i} \\ \Lambda_{\rho u} \\ \Lambda_{\rho E} \end{pmatrix} = - \begin{pmatrix} \frac{\partial f}{\partial \rho_i} \\ \frac{\partial f}{\partial \rho u} \\ \frac{\partial f}{\partial \rho E} \end{pmatrix}$$

- Can be solved with Krylov method (i.e. GMRES), but time marching similar to flow solver shown to be more robust

$$\left(\frac{V}{\Delta t} \mathbf{I} + \frac{\partial \mathbf{R}_1}{\partial \mathbf{Q}}^T \right) \Delta \Lambda = - \frac{\partial f}{\partial \mathbf{Q}} - \frac{\partial \mathbf{R}_2}{\partial \mathbf{Q}}^T \Lambda^n$$

- Straightforward to formulate, but cost and memory requirements scale quadratically with number of species

Decoupled Adjoint Scheme

- The decoupled flow solver has an analog in the adjoint
- First, recognize that the decoupled flow solver can be rewritten as a fully coupled system, with a change of variables and change of equations

$$\underbrace{\mathbf{U} = \begin{pmatrix} \rho_1 \\ \vdots \\ \rho_{ns} \\ \rho \mathbf{u} \\ \rho E \end{pmatrix} \rightarrow \mathbf{V} = \begin{pmatrix} c_1 \\ \vdots \\ c_{ns} \\ \rho \\ \rho \mathbf{u} \\ \rho E \end{pmatrix}}_{\text{Change of Variables}}, \quad \underbrace{\mathbf{R}_U = \begin{pmatrix} \mathbf{R}_{\rho_1} \\ \vdots \\ \mathbf{R}_{\rho_{N_s}} \\ \mathbf{R}_{\rho \mathbf{u}} \\ \mathbf{R}_{\rho E} \end{pmatrix} \rightarrow \mathbf{R}_V = \begin{pmatrix} \mathbf{R}_{\rho_1} - c_1 \sum_{i=1}^{N_s} (\mathbf{R}_{\rho_i}) \\ \vdots \\ \mathbf{R}_{\rho_{N_s}} - c_{N_s} \sum_{i=1}^{N_s} (\mathbf{R}_{\rho_i}) \\ \sum_{i=1}^{N_s} (\mathbf{R}_{\rho_i}) \\ \mathbf{R}_{\rho \mathbf{u}} \\ \mathbf{R}_{\rho E} \end{pmatrix}}_{\text{Change of Equations}}$$

$$c_s = \frac{\rho_s}{\rho}, \quad \rho = \sum_{i=1}^{N_s} (\rho_i)$$

Decoupled Adjoint Scheme

- This change of variables/equations results in non-square transformation matrices

$$\frac{\partial \mathbf{U}}{\partial \mathbf{V}} = \begin{pmatrix} \rho & \dots & 0 & c_1 & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ 0 & \dots & \rho & c_{ns} & 0 & 0 \\ 0 & \dots & 0 & 0 & 1 & 0 \\ 0 & \dots & 0 & 0 & 0 & 1 \end{pmatrix}, \quad \frac{\partial \mathbf{R}_V}{\partial \mathbf{R}_U} = \begin{pmatrix} 1 - c_1 & -c_1 & \dots & -c_1 & 0 & 0 \\ -c_2 & 1 - c_2 & \dots & -c_2 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ -c_{N_s} & -c_{N_s} & \dots & 1 - c_{N_s} & 0 & 0 \\ 1 & 1 & \dots & 1 & 0 & 0 \\ 0 & 0 & \dots & 0 & 1 & 0 \\ 0 & 0 & \dots & 0 & 0 & 1 \end{pmatrix}$$

Decoupled Adjoint Scheme

- Using the transformation matrices, $\frac{\partial \mathbf{U}}{\partial \mathbf{V}}$ and $\frac{\partial \mathbf{R}_U}{\partial \mathbf{R}_V}$, it possible to treat the decoupled approach as a series of matrix operations

$$\frac{\partial \mathbf{R}_V}{\partial \mathbf{V}} = \frac{\partial \mathbf{R}_V}{\partial \mathbf{R}_U} \frac{\partial \mathbf{R}_U}{\partial \mathbf{U}} \frac{\partial \mathbf{U}}{\partial \mathbf{V}}$$

Decoupled Adjoint Scheme

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$$\frac{\partial \mathbf{R}_\mathbf{V}}{\partial \mathbf{V}} = \frac{\partial \mathbf{R}_\mathbf{V}}{\partial \mathbf{R}_\mathbf{U}} \frac{\partial \mathbf{R}_\mathbf{U}}{\partial \mathbf{U}} \frac{\partial \mathbf{U}}{\partial \mathbf{V}}$$

- These matrix operations can be thought of as left and right preconditioning

$$\frac{\partial \mathbf{R}_\mathbf{V}}{\partial \mathbf{V}} = \underbrace{\left(\frac{\partial \mathbf{R}_\mathbf{V}}{\partial \mathbf{R}_\mathbf{U}} \right)}_{\text{Left Preconditioner}} \underbrace{\left(\frac{\partial \mathbf{R}_\mathbf{U}}{\partial \mathbf{U}} \right)}_{\text{Right Preconditioner}} \underbrace{\left(\frac{\partial \mathbf{U}}{\partial \mathbf{V}} \right)}$$

Decoupled Adjoint Scheme

- Using the transformation matrices, $\frac{\partial \mathbf{U}}{\partial \mathbf{V}}$ and $\frac{\partial \mathbf{R}_\mathbf{U}}{\partial \mathbf{R}_\mathbf{V}}$, it possible to treat the decoupled approach as a series of matrix operations

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- This transformation avoids having to explicitly form the jacobian $\frac{\partial \mathbf{R}_\mathbf{V}}{\partial \mathbf{V}}$, which are complicated than $\frac{\partial \mathbf{R}_\mathbf{U}}{\partial \mathbf{U}}$

Decoupled Adjoint Scheme

- Rewrite the adjoint system from $\mathbf{R}_{\mathbf{V}}(\mathbf{V})$

$$\left(\frac{\partial \mathbf{R}_{\mathbf{V}}}{\partial \mathbf{V}} \right)^T \boldsymbol{\Lambda}_{\mathbf{V}} = - \frac{\partial f}{\partial \mathbf{V}}$$

Decoupled Adjoint Scheme

- Rewrite the adjoint system from $\mathbf{R}_V(\mathbf{V}) \rightarrow \mathbf{R}_U(\mathbf{U})$

$$\left(\frac{\partial \mathbf{R}_V}{\partial \mathbf{V}}\right)^T \Lambda_V = -\frac{\partial f}{\partial \mathbf{V}}$$
$$\left(\frac{\partial \mathbf{U}}{\partial \mathbf{V}}\right)^T \left(\frac{\partial \mathbf{R}_U}{\partial \mathbf{U}}\right)^T \left(\frac{\partial \mathbf{R}_V}{\partial \mathbf{R}_U}\right)^T \Lambda_V = -\left(\frac{\partial \mathbf{U}}{\partial \mathbf{V}}\right)^T \left(\frac{\partial f}{\partial \mathbf{U}}\right)$$

Decoupled Adjoint Scheme

- Rewrite the adjoint system from $\mathbf{R}_V(\mathbf{V}) \rightarrow \mathbf{R}_U(\mathbf{U})$

$$\left(\frac{\partial \mathbf{R}_V}{\partial \mathbf{V}}\right)^T \Lambda_V = -\frac{\partial f}{\partial \mathbf{V}}$$
$$\left(\frac{\partial \mathbf{U}}{\partial \mathbf{V}}\right)^T \left(\frac{\partial \mathbf{R}_U}{\partial \mathbf{U}}\right)^T \left(\frac{\partial \mathbf{R}_V}{\partial \mathbf{R}_U}\right)^T \Lambda_V = -\left(\frac{\partial \mathbf{U}}{\partial \mathbf{V}}\right)^T \left(\frac{\partial f}{\partial \mathbf{U}}\right)$$

- Effectively another Left/Right Preconditioning

$$\underbrace{\left(\frac{\partial \mathbf{U}}{\partial \mathbf{V}}\right)^T}_{\text{Left Preconditioning}} \underbrace{\left(\frac{\partial \mathbf{R}_U}{\partial \mathbf{U}}\right)^T \left(\frac{\partial \mathbf{R}_V}{\partial \mathbf{R}_U}\right)^T}_{\text{Right Preconditioning}} \Lambda_V = - \underbrace{\left(\frac{\partial \mathbf{U}}{\partial \mathbf{V}}\right)^T}_{\text{Left Preconditioning}} \left(\frac{\partial f}{\partial \mathbf{U}}\right)$$
$$\left(\frac{\partial \mathbf{R}_V}{\partial \mathbf{R}_U}\right)^T \Lambda_V = \Lambda_U$$

Decoupled Adjoint Solver

- Time march adjoint solution with approximate jacobians

$$\left(\frac{V}{\Delta t} \mathbf{I} + \frac{\partial \mathbf{R}_{\mathbf{v}_1}}{\partial \mathbf{V}}^T \right) \Lambda_{\mathbf{V}} = - \left(\frac{\partial \mathbf{U}}{\partial \mathbf{V}} \right)^T \underbrace{\left(\frac{\partial \mathbf{R}_{\mathbf{u}_2}}{\partial \mathbf{U}} \Lambda_{\mathbf{U}} + \frac{\partial f}{\partial \mathbf{U}} \right)}_{\text{Fully Coupled Residual}}$$

- Split $\frac{\partial \mathbf{R}_{\mathbf{v}_1}}{\partial \mathbf{V}}$ in same fashion as flow solver

Decoupled Adjoint Solver

- Time march adjoint solution with approximate jacobians

$$\left(\frac{V}{\Delta t} \mathbf{I} + \frac{\partial \mathbf{R}_{\mathbf{v}_1}}{\partial \mathbf{V}}^T \right) \Lambda_{\mathbf{v}} = - \underbrace{\left(\frac{\partial \mathbf{U}}{\partial \mathbf{V}} \right)^T \left(\frac{\partial \mathbf{R}_{\mathbf{u}_2}}{\partial \mathbf{U}} \Lambda_{\mathbf{u}} + \frac{\partial f}{\partial \mathbf{U}} \right)}_{\text{Fully Coupled Residual}}$$

- Split $\frac{\partial \mathbf{R}_{\mathbf{v}_1}}{\partial \mathbf{V}}$ in same fashion as flow solver

$$\begin{pmatrix} \frac{\partial \mathbf{R}'_{\rho_1}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}'_{\rho_1}}{\partial c_{N_s}} & \frac{\partial \mathbf{R}'_{\rho_1}}{\partial \rho} & \frac{\partial \mathbf{R}'_{\rho_1}}{\partial \rho \mathbf{u}} & \frac{\partial \mathbf{R}'_{\rho_1}}{\partial \rho E} \\ \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ \frac{\partial \mathbf{R}'_{\rho N_s}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}'_{\rho N_s}}{\partial c_{N_s}} & \frac{\partial \mathbf{R}'_{\rho N_s}}{\partial \rho} & \frac{\partial \mathbf{R}'_{\rho N_s}}{\partial \rho \mathbf{u}} & \frac{\partial \mathbf{R}'_{\rho N_s}}{\partial \rho E} \\ \frac{\partial \mathbf{R}_{\rho}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}_{\rho}}{\partial c_{N_s}} & \frac{\partial \mathbf{R}_{\rho}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho}}{\partial \rho \mathbf{u}} & \frac{\partial \mathbf{R}_{\rho}}{\partial \rho E} \\ \frac{\partial \mathbf{R}_{\rho \mathbf{u}}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}_{\rho \mathbf{u}}}{\partial c_{N_s}} & \frac{\partial \mathbf{R}_{\rho \mathbf{u}}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho \mathbf{u}}}{\partial \rho \mathbf{u}} & \frac{\partial \mathbf{R}_{\rho \mathbf{u}}}{\partial \rho E} \\ \frac{\partial \mathbf{R}_{\rho E}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}_{\rho E}}{\partial c_{N_s}} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho \mathbf{u}} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho E} \end{pmatrix}$$

Decoupled Adjoint Solver

- Time march adjoint solution with approximate jacobians

$$\left(\frac{V}{\Delta t} \mathbf{I} + \frac{\partial \mathbf{R}_{\mathbf{V}_1}}{\partial \mathbf{V}}^T \right) \Lambda_{\mathbf{V}} = - \underbrace{\left(\frac{\partial \mathbf{U}}{\partial \mathbf{V}} \right)^T \left(\frac{\partial \mathbf{R}_{\mathbf{U}_2}}{\partial \mathbf{U}} \Lambda_{\mathbf{U}} + \frac{\partial f}{\partial \mathbf{U}} \right)}_{\text{Fully Coupled Residual}}$$

- Split $\frac{\partial \mathbf{R}_{\mathbf{V}_1}}{\partial \mathbf{V}}$ in same fashion as flow solver

$$\begin{pmatrix} \boxed{\begin{matrix} \frac{\partial \mathbf{R}'_{\rho_1}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}'_{\rho_1}}{\partial c_{N_S}} \\ \vdots & \ddots & \vdots \\ \frac{\partial \mathbf{R}'_{\rho_{N_S}}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}'_{\rho_{N_S}}}{\partial c_{N_S}} \end{matrix}} & \begin{matrix} \frac{\partial \mathbf{R}'_{\rho_1}}{\partial \rho} & \frac{\partial \mathbf{R}'_{\rho_1}}{\partial \rho u} & \frac{\partial \mathbf{R}'_{\rho_1}}{\partial \rho E} \\ \vdots & \vdots & \vdots \end{matrix} \\ \begin{matrix} \frac{\partial \mathbf{R}_{\rho}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}_{\rho}}{\partial c_{N_S}} \\ \frac{\partial \mathbf{R}_{\rho u}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}_{\rho u}}{\partial c_{N_S}} \\ \frac{\partial \mathbf{R}_{\rho E}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}_{\rho E}}{\partial c_{N_S}} \end{matrix} & \boxed{\begin{matrix} \frac{\partial \mathbf{R}_{\rho}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho}}{\partial \rho u} & \frac{\partial \mathbf{R}_{\rho}}{\partial \rho E} \\ \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho u} & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho E} \\ \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho u} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho E} \end{matrix}} \end{pmatrix}$$

Decoupled Adjoint Solver

- Time march adjoint solution with approximate jacobians

$$\left(\frac{V}{\Delta t} \mathbf{I} + \frac{\partial \mathbf{R}_{\mathbf{V}_1}}{\partial \mathbf{V}}^T \right) \Lambda_{\mathbf{V}} = - \left(\frac{\partial \mathbf{U}}{\partial \mathbf{V}} \right)^T \underbrace{\left(\frac{\partial \mathbf{R}_{\mathbf{U}_2}}{\partial \mathbf{U}} \Lambda_{\mathbf{U}} + \frac{\partial f}{\partial \mathbf{U}} \right)}_{\text{Fully Coupled Residual}}$$

- Split $\frac{\partial \mathbf{R}_{\mathbf{V}_1}}{\partial \mathbf{V}}$ in same fashion as flow solver

$$\begin{pmatrix} \boxed{\begin{matrix} \frac{\partial \mathbf{R}'_{\rho_1}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}'_{\rho_1}}{\partial c_{N_s}} \\ \vdots & \ddots & \vdots \\ \frac{\partial \mathbf{R}'_{\rho_{N_s}}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}'_{\rho_{N_s}}}{\partial c_{N_s}} \end{matrix}} & \begin{matrix} \frac{\partial \mathbf{R}'_{\rho_1}}{\partial \rho} & \frac{\partial \mathbf{R}'_{\rho_1}}{\partial \rho u} & \frac{\partial \mathbf{R}'_{\rho_1}}{\partial \rho E} \\ \vdots & \vdots & \vdots \\ \frac{\partial \mathbf{R}'_{\rho_{N_s}}}{\partial \rho} & \frac{\partial \mathbf{R}'_{\rho_{N_s}}}{\partial \rho u} & \frac{\partial \mathbf{R}'_{\rho_{N_s}}}{\partial \rho E} \end{matrix} \\ \begin{matrix} \frac{\partial \mathbf{R}_{\rho}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}_{\rho}}{\partial c_{N_s}} \\ \frac{\partial \mathbf{R}_{\rho u}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}_{\rho u}}{\partial c_{N_s}} \\ \frac{\partial \mathbf{R}_{\rho E}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}_{\rho E}}{\partial c_{N_s}} \end{matrix} & \boxed{\begin{matrix} \frac{\partial \mathbf{R}_{\rho}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho}}{\partial \rho u} & \frac{\partial \mathbf{R}_{\rho}}{\partial \rho E} \\ \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho u} & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho E} \\ \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho u} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho E} \end{matrix}} \end{pmatrix} \rightarrow \begin{pmatrix} \frac{\partial \mathbf{R}_{\rho_1}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}_{\rho_1}}{\partial c_{N_s}} \\ \vdots & \ddots & \vdots \\ \frac{\partial \mathbf{R}_{\rho_{N_s}}}{\partial c_1} & \cdots & \frac{\partial \mathbf{R}_{\rho_{N_s}}}{\partial c_{N_s}} \end{pmatrix}, \begin{pmatrix} \frac{\partial \mathbf{R}_{\rho}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho}}{\partial \rho u} & \frac{\partial \mathbf{R}_{\rho}}{\partial \rho E} \\ \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho u} & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho E} \\ \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho u} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho E} \end{pmatrix}$$

Species Equations

Mixture Equations

Decoupled Adjoint Solver

- Separate into two systems and solve as block jacobi scheme

$$\left(\frac{\rho V}{\Delta t} \mathbf{I} + \frac{\partial \mathbf{R}_{\mathbf{V}_i}}{\partial c_s} \right) \Delta \Lambda_{\mathbf{V}_{c_i}} = -\rho \left(\frac{\partial f}{\partial \rho_s} + \frac{\partial \mathbf{R}_{\mathbf{U}}}{\partial \rho_s} \Lambda_{\mathbf{U}} \right)$$

$$\left[\frac{V}{\Delta t} \mathbf{I} + \begin{pmatrix} \frac{\partial \mathbf{R}_{\rho}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho} \\ \frac{\partial \mathbf{R}_{\rho}}{\partial \rho u} & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho u} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho u} \\ \frac{\partial \mathbf{R}_{\rho}}{\partial \rho E} & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho E} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho E} \end{pmatrix} \right] \begin{pmatrix} \Delta \Lambda_{\mathbf{V}_{\rho}} \\ \Delta \Lambda_{\mathbf{V}_{\rho u}} \\ \Delta \Lambda_{\mathbf{V}_{\rho E}} \end{pmatrix} =$$

$$- \begin{pmatrix} \frac{\partial f}{\partial \rho} \\ \frac{\partial f}{\partial \rho u} \\ \frac{\partial f}{\partial \rho E} \end{pmatrix} - \begin{pmatrix} \frac{\partial \mathbf{R}_{\rho}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho} \\ \frac{\partial \mathbf{R}_{\rho}}{\partial \rho u} & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho u} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho u} \\ \frac{\partial \mathbf{R}_{\rho}}{\partial \rho E} & \frac{\partial \mathbf{R}_{\rho u}}{\partial \rho E} & \frac{\partial \mathbf{R}_{\rho E}}{\partial \rho E} \end{pmatrix} \begin{pmatrix} \Lambda_{\rho} \\ \Lambda_{\rho u} \\ \Lambda_{\rho E} \end{pmatrix} - \begin{pmatrix} \frac{\partial \mathbf{R}_{\rho}}{\partial c_s} \\ \frac{\partial \mathbf{R}_{\rho u}}{\partial c_s} \\ \frac{\partial \mathbf{R}_{\rho E}}{\partial c_s} \end{pmatrix}^T \Lambda_{c_s}$$