

# Comparison of $h$ - and $p$ -Derived Output-Based Error Estimates for Directing Anisotropic Adaptive Mesh Refinement in Three-Dimensional Inviscid Flows

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# Introduction and Motivation

## Computational Fluid Dynamics (CFD)

- Increase in computer memory and processing power.
- CFD - capture complex phenomena. {Parallel algorithms, accuracy, computational time, costs?}
- To reduce memory & storage requirements, utilize local anisotropic block-based adaptive mesh refinement (AMR) of Freret and Groth [2015].
- AMR originally driven by physics-based criteria. Limitations in solution accuracy.

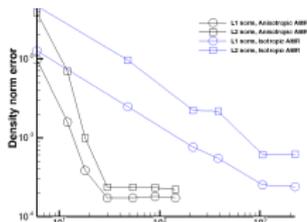


Figure 1.1: Error in the density norm for steady supersonic flow over a sphere. [Freret and Groth 2015]

## Goal of this work

- Find a metric relating functional to solution error.
- Output-based error estimation for anisotropic block-based AMR .
- Benefits and associated computational cost?
- Calculate error estimates in two ways:
  - $h$ -derived error estimates: via refining the mesh.
  - $p$ -derived error estimates: by increasing the order of discretization.

by reconstructing the solution,  $\mathbf{U}$  and solution residual,  $\mathbf{R}(\mathbf{U})$ .

# Euler equations

$$\frac{\partial \mathbf{U}}{\partial t} = - \left[ \frac{\partial \mathbf{F}}{\partial x} + \frac{\partial \mathbf{G}}{\partial y} + \frac{\partial \mathbf{H}}{\partial z} \right] = -\mathbf{R}(\mathbf{U}) = 0,$$

- vectors  $\mathbf{F}$ ,  $\mathbf{G}$ ,  $\mathbf{H}$   $\rightarrow$  inviscid flux vectors associated with the solution flux in the  $x$ ,  $y$ , and  $z$  directions respectively.
- Ideal gas equation of state  $p = \rho RT$  is used to close the system.

## Limited $2^{nd}$ order FVM

$$\frac{d\bar{\mathbf{U}}_{ijk}}{dt} = - \frac{1}{V_{ijk}} \oint_{\partial V} \bar{\mathbf{F}} \cdot \bar{\mathbf{n}} da = \mathbf{R}_{ijk}(\bar{\mathbf{U}})$$

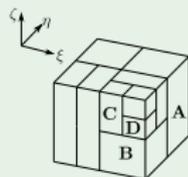
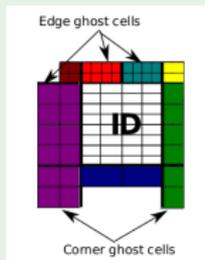
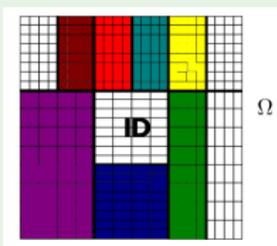
- Limited linear least-squares method for solution reconstruction.
- Solution space is enriched from coarse ( $\Omega_H$ ) to fine ( $\Omega_h$ ).

## CENO - [Ivan and Groth 2014]

$$\frac{d\bar{\mathbf{U}}_{ijk}}{dt} = - \frac{1}{V_{ijk}} \sum_{f=1}^{N_f} \sum_{m=1}^{N_G} (\omega \bar{\mathbf{F}} \cdot \hat{\mathbf{n}} A)_{ijk,f,m} = \bar{\mathbf{R}}_{ijk}(\bar{\mathbf{U}})$$

- unlimited  $k$ -exact reconstruction - smooth solution.
- low-order for non-smooth content.
- Smoothness indicator used to ensure monotonicity.
- Solution space from coarse ( $\Omega_P$ ) to fine ( $\Omega_p$ ).
- store relevant num of derivatives for high-order solution.

## Domain Decomposition & AMR [Freret *et al.* 2017, Freret and Groth 2015]



$\xi$  Split ———  
 $\eta$  Split .....  
 $\zeta$  Split - - - - -

Solve the governing equations to obtain a converged primal solution,  $-\mathbf{R}(\mathbf{U}) = 0$

Define an engineering functional of interest,  $J(\mathbf{U})$ .

Discrete Adjoint ( $\Psi$ ) measures functional sensitivity to the solution residual,  $\mathbf{R}(\mathbf{U})$ :

$$\left(\frac{\partial \mathbf{R}}{\partial \mathbf{U}}\right)^T \Psi = -\left(\frac{\partial J}{\partial \mathbf{U}}\right)^T$$

$\mathbf{U}_h$  is expensive to solve. Instead, approximate by  $\mathbf{U}_h^H$ .

The error in the functional is given in the approximation:

$$\delta J = J_h(\mathbf{U}_h^H) - J_h(\mathbf{U}_h) \approx \underbrace{(\Psi_h^H)^T \mathbf{R}_h(\mathbf{U}_h^H)}_{\text{computable correction}} + \underbrace{(\mathbf{R}_h^\Psi(\Psi_h^H))^T (\mathbf{U}_h - \mathbf{U}_h^H)}_{\text{error in computable correction}}$$

$\mathcal{E}_{K_H}$  based on CC

$$\mathcal{E}_{K_H} = \sum_{l(k)} \left\{ \left| (\Psi_h^H)^T \mathbf{R}_h(\mathbf{U}_h^H) \right|_{l(k)} \right\}$$

$\mathcal{E}_{K_{H,P}}$  based on CC

$$\mathcal{E}_{K_{H,P}} = \left| (\Psi_{H,P}^P)^T \mathbf{R}_{H,P}(\mathbf{U}_{H,P}^P) \right|$$

$\mathcal{E}_{K_H}$  based on ECC

$$\mathcal{E}_{K_H} = \sum_{l(k)} \left\{ \frac{1}{2} \left| \left[ \mathbf{Q}_h^H \Psi_H - \mathbf{L}_h^H \Psi_H \right]_{l(k)}^T \left[ \mathbf{R}_h(\mathbf{L}_h^H \mathbf{U}_H) \right]_{l(k)} \right| + \frac{1}{2} \left| \left[ \mathbf{Q}_h^H \mathbf{U}_H - \mathbf{L}_h^H \mathbf{U}_H \right]_{l(k)}^T \left[ \mathbf{R}_h^\Psi(\mathbf{L}_h^H \Psi_H) \right]_{l(k)} \right| \right\}$$

$\mathcal{E}_{K_{H,P}}$  based on ECC

$$\mathcal{E}_{K_{H,P}} = \frac{1}{2} \left| \left[ \Psi_{H,P}^P - \Psi_{H,P} \right] \left[ \mathbf{R}_{H,P}(\mathbf{U}_{H,P}^P) \right] \right| + \frac{1}{2} \left| \left[ \mathbf{U}_{H,P}^P - \mathbf{U}_{H,P} \right] \left[ \mathbf{R}_{H,P}^\Psi(\Psi_{H,P}^P) \right] \right|$$

## Gradient-based

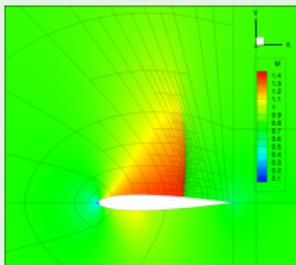


Figure 1.1: Close-up showing final gradient-based AMR mesh, 435 blocks (445,440 cells).

## Output-based

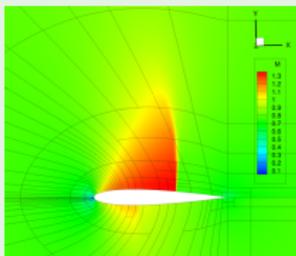


Figure 1.2: Close-up showing final output-based AMR mesh, via  $p$ -derived ECC-based error indicator, 259 blocks (= 265,216 cells), representing 40% cell count savings.

## Functional accuracy vs. mesh size

