

A Framework for Analyzing and Constructing Hierarchical-Type A Posteriori Error Estimators

Jeff Ovall University of Kentucky Mathematics www.math.uky.edu/~jovall jovall@ms.uky.edu



Introduction, Motivation



Mouse Acetylcholinesterase (mAChE) Monomer, 8362 Atoms



Sandia Long-life Thermal Battery



Model Problem

Setting

- $\Omega \subset \mathbb{R}^d$ (d = 2, 3), bounded, polyhedral
- $\Gamma = \partial \Omega = \Gamma_D \cup \Gamma_N$, $\Gamma_D \cap \Gamma_N = \emptyset$
- $\mathcal{H} = \{ v \in H^1(\Omega) : v = 0 \text{ on } \Gamma_D \text{ in the trace sense} \}$

Variational Problem

Find $u \in \mathcal{H}$ such that

$$\underbrace{\int_{\Omega} (A\nabla u) \cdot \nabla v + (\mathbf{b} \cdot \nabla u + cu) v \, dV}_{B(u,v)} = \underbrace{\int_{\Omega} fv \, dV + \int_{\Gamma_N} gv \, dS}_{F(v)}, \ \forall v \in \mathcal{H}$$

• $|B(v,w)| \leq M \|v\|_1 \|w\|_1$, $B(v,v) \geq m \|v\|_1^2$

(can have inf-sup instead)

- $|F(v)| \leq L ||v||_1$
- Piecewise-smooth data, A, \mathbf{b}, c, f, g



Finite Element Discretization

Approximation Space:

- Mesh \mathcal{T} : Conforming simplicial partition (triangles in \mathbb{R}^2 , tetrahedra in \mathbb{R}^3)
 - Simplices T: align with discontinuities in data A, b, c, f, g
 - Vertices z: all $\overline{\mathcal{V}}$, non-Dirichlet \mathcal{V} , Dirichlet \mathcal{V}_D
 - Edges E: all $\overline{\mathcal{E}}$, non-Dirichlet \mathcal{E} , Dirichlet \mathcal{E}_D
 - Faces F: all $\overline{\mathcal{F}}$, non-Dirichlet \mathcal{F} , Dirichlet \mathcal{F}_D
- Approximation Space V: piecewise polynomials of a fixed degree k

 $V = \mathbb{P}_k(\mathcal{T}) = \{ v \in \mathcal{H} \cap C(\overline{\Omega}) : v|_T \in \mathbb{P}_k \text{ for all } T \in \mathcal{T} \}$

Discrete Approximation Problem:

- $V = \operatorname{span}\{\phi_j : 1 \le j \le N\}$, ϕ_j locally-supported
- Find $\hat{u} \in V$ such that $B(\hat{u}, v) = F(v)$ for all $v \in V$
- $B\mathbf{u} = \mathbf{f}$ where $B_{ij} = B(\phi_j, \phi_i)$ and $\mathbf{f}_i = F(\phi_i)$
- *B* large, sparse, but ill-conditioned ($\kappa(B) \sim N^{2/d} \sim h^{-2}$)



Motivation for A Posteriori Error Estimation and Adaptivity

Approximation Quality $\hat{u} \approx u$

 $B(u-\hat{u},v) = 0 \text{ for all } v \in V \implies ||u-\hat{u}||_1 \leq C \inf_{v \in V} ||u-v||_1$

- Discretization error comparable to interpolation error
- Interpolation error related to regularity/smoothness of u
- Efficiently and reliably identify problem areas and adaptively improve
 - $\cdots \longrightarrow \mathsf{solve} \longrightarrow \mathsf{estimate} \mathsf{ error} \longrightarrow \mathsf{mark} \mathsf{ elements} \longrightarrow \mathsf{refine} \longrightarrow \cdots$

Common Causes of Singularities in \boldsymbol{u}

- (Re-entrant) corners and/or edges in domain
- Changes in boundary condition type (Dirichlet-Neumann interface)
- Discontinuities in problem data (abrupt changes in material properties)



Types of Error Estimators on the Market

- Residual: Appropriate weighting of volumetric and "jump" portions of strong residual
 - Oldest, most fully developed (reliablility and convergence) theory
- Gradient Recovery: Post-processing of $abla \hat{u}$ by local or global "averaging"
 - Problem-independent approach, popular in (some) engineering circles
 - Sometimes see (more often than is currently explainable) asymptotically exact estimation of error—super-convergence, strong smoothness assumptions
- Hierarchical Type: Approximate error function computed in an auxiliary space
 - Very robust and flexible, often see gradient recovery-type performance
 - Too expensive? I will argue "no"—certainly not for what you get
- Other Types used for Norm-Error Estimation: Equilibrated Residual, others based on solution of local Dirichlet and/or Neumann problems
- Functional Error Estimation, Goal-Oriented Adaptivity: functional error $G(u \hat{u})$ of interest
 - Many above types can be modified to work in this setting



Abstract View of Hierarchical Error Estimators

Original Problem

Find
$$u \in \mathcal{H}$$
 such that $B(u, v) = F(v)$ for all $v \in \mathcal{H}$

Discrete Problem

Find $\hat{u} \in V$ such that $B(\hat{u}, v) = F(v)$ for all $v \in V$

Discrete Error Problem

Find $\varepsilon \in W$ such that $B(\varepsilon, v) = F(v) - B(\hat{u}, v) = B(u - \hat{u}, v)$ for all $v \in W$

Some Common Choices for V, W:

- $V = \mathbb{P}_k(\mathcal{T}), W = \mathbb{P}_{k+1}(\mathcal{T}) \setminus \mathbb{P}_k(\mathcal{T})$
- $V = \mathbb{P}_k(\mathcal{T}), W = \mathbb{P}_k(\mathcal{T}') \setminus \mathbb{P}_k(\mathcal{T}), \mathcal{T}'$ from uniform refinement(s) of \mathcal{T}



An Example in 2D—Thermal Battery Problem



Sandia Long-life Thermal Battery

Use radial symmetry, convert to 2D $V = \mathbb{P}_1(\mathcal{T})$, $W = \mathbb{P}_2(\mathcal{T}) \setminus \mathbb{P}_1(\mathcal{T})$







Thermal Battery Problem: HB versus GR Refinement





A Framework for Constructing and Analyzing Hierarchical Estimators





The Traditional Analysis

See Bank (Acta Numerica '96), or Ainsworth&Oden book

Setting/Assumptions

- B is an inner-product (no convection), energy norm $||| \cdot ||$
- $V \cap W = \{0\}$, and V contains local constants (quite sensible)
- Strong Cauchy Inquality: $|B(v,w)| \le \gamma ||v|| ||w|||$ for $v \in V$ and $w \in W$, where $\gamma = \gamma(B,V,W) < 1$
- Saturation Assumption: $\inf_{v \in V \oplus W} |||u v||| \le \beta \inf_{v \in V} |||u v|||$, where $\beta = \beta(B, V, W, F) < 1$
 - This assumption "compels" one to choose W so that $V\oplus W$ is a natural approximation space

$$\| arepsilon \| \le \| u - \hat{u} \| \le \left((1 - \gamma^2) (1 - \beta^2)
ight)^{-1/2} \| arepsilon \|$$



A Different Approach to the Analysis

See Grubisic/Ovall (MC 2009), Holst/Ovall/Szypowski (APNUM 2011), Bank/Grubisic/Ovall (MC 2011??),

New Approach: For any $v \in \mathcal{H}$, $\hat{v} \in V$ and $\hat{w} \in W$,

$$B(u - \hat{u}, v) = B(\varepsilon, \hat{w}) + B(u - \hat{u}, v - \hat{v} - \hat{w})$$

= $B(\varepsilon, \hat{w}) + [F(v - \hat{v} - \hat{w}) - B(\hat{u}, v - \hat{v} - \hat{w})]$

$$|B(u - \hat{u}, v)| \leq [C_1 \|arepsilon\| + C_2$$
 "residual oscillation"] $\|v\|$

 $K_0 \|\varepsilon\| \le \|u - \hat{u}\| \le K_1 \|\varepsilon\| + K_2$ "residual oscillation"

- Not necessarily in energy-norm setting; always true (not just asymptotic); only H^1 -regularity assumption on u
- Constants scale-invariant; clear what they depend on and how—do not depend on *F*!!
- Choose space W, and then \hat{v}, \hat{w} , to make residual oscillation small
 - $\hat{v}+\hat{w}$ a well-chosen quasi-interpolant
 - Local vanishing moments for $v (\hat{v} + \hat{w})$
- Choose space W so that computation of ε is cheap



The Error Equation Revisited:

$$\begin{split} B(u-\hat{u},v) &= B(\varepsilon,w) + \left[F(v-\hat{v}-\hat{w}) - B(\hat{u},v-\hat{v}-\hat{w})\right] \\ &= B(\varepsilon,\hat{w}) + \int_{\Omega} (f-\mathbf{b}\cdot\nabla\hat{u}-c\hat{u})(v-\hat{v}-\hat{w}) - A\nabla\hat{u}\cdot\nabla(v-\hat{v}-\hat{w}) \, dx \\ &+ \int_{\Gamma_N} (g-A\nabla\hat{u}\cdot\mathbf{n})(v-\hat{v}-\hat{w}) \, ds \\ &= B(\varepsilon,\hat{w}) + \int_{\Omega} R(v-\hat{v}-\hat{w}) \, dx + \sum_{F\in\mathcal{F}} \int_F r(v-\hat{v}-\hat{w}) \, ds \end{split}$$

$$R_{|_{T}} = f - (-\nabla \cdot A\nabla \hat{u} + \mathbf{b} \cdot \nabla \hat{u} + c\hat{u})$$
$$r_{|_{F}} = \begin{cases} -(A\nabla \hat{u}) \cdot \mathbf{n}_{T} - (A\nabla \hat{u}) \cdot \mathbf{n}_{T'} &, F \in \mathcal{F}_{I} \\ g - (A\nabla \hat{u}) \cdot \mathbf{n} &, F \in \mathcal{F}_{N} \end{cases}$$

Kentucky Applied and Computational Math Group



Approximation Space:

•
$$V = \mathbb{P}_1(\mathcal{T}) = \operatorname{span}\{\ell_z : z \in \mathcal{V}\}, \ \ell_z(z') = \delta_{zz'} \text{ for all } z, z' \in \overline{\mathcal{V}}\}$$

• A (non-smooth) partition-of-unity $\sum_{z\in\overline{\mathcal{V}}}\ell_z=1$ on Ω

• $\omega_z \doteq \operatorname{supp}(\ell_z)$

Error Equation (Again):

$$B(u-\hat{u},v) = B(\varepsilon,w) + \sum_{z\in\overline{\mathcal{V}}}\int_{\Omega} R(v\ell_z - \hat{v}_z - \hat{w}_z) \, dx + \sum_{F\in\mathcal{F}}\int_F r(v-\hat{v}-\hat{w}) \, ds$$

•
$$\hat{v} = \sum_{z \in \overline{\mathcal{V}}} v_z$$
, $\hat{w} = \sum_{z \in \overline{\mathcal{V}}} w_z$ \hat{v}_z , \hat{w}_z locally supported

• How to choose error space W? functions v_z , w_z ?



$$B(u-\hat{u},v) = B(\varepsilon,w) + \sum_{z\in\overline{\mathcal{V}}}\int_{\Omega} R(v\ell_z - \hat{v}_z - \hat{w}_z) \, dx + \sum_{F\in\mathcal{F}}\int_F r(v-\hat{v}-\hat{w}) \, ds$$

A Useful Quasi-Interpolant: $\mathcal{I}v = \hat{v} + \hat{w} \in V \oplus W$

$$\int_{\Omega} (v\ell_z - v_z - w_z) = 0 \text{ for all } z \in \overline{\mathcal{V}} \quad , \quad \int_F (v - \hat{v} - \hat{w}) = 0 \text{ for all } F \in \mathcal{F}$$
(1)

$$\mathsf{supp}(v_z)\,,\,\mathsf{supp}(w_z)\subset\Omega_z=egin{cases} \omega_z&,\,\,z\in\mathcal{V}\ \omega_z\cup\omega_{z'}\ ext{for some }z'\in\mathcal{V}\ \mathsf{adjacent\ to\ }z\quad,\,z\in\mathcal{V}_D \end{cases}$$

Choosing W:

- A space W providing a single degree-of-freedom for each $F \in \mathcal{F}$ is sufficient for (1)
- We choose W ⊂ P₃(T) consisting of functions vanishing on every edge (cubic "face bubbles")
- $V \oplus W$ is *not* a standard approximation space



$$||u - \hat{u}||_1 \le K_1 ||\varepsilon||_1 + K_2 \operatorname{osc}(R, r)$$

Reliability Argument:

$$\begin{split} |B(u-\hat{u},v)| &\leq M \|\varepsilon\|_{1} \|\hat{w}\|_{1} + \sum_{z\in\bar{\mathcal{V}}} \inf_{R_{z}\in\mathbb{R}} \|R-R_{z}\|_{0,\Omega_{z}} \|v\ell_{z}-v_{z}-w_{z}\|_{0,\Omega_{z}} \\ &+ \sum_{F\in\mathcal{F}} \inf_{r_{F}\in\mathbb{R}} \|r-r_{F}\|_{0,F} \|v-\hat{v}-\hat{w}\|_{0,F} \\ |B(u-\hat{u},v)| &\leq C_{1} \|\varepsilon\|_{1} \|v\|_{1} + C_{21} \sum_{z\in\bar{\mathcal{V}}} D_{z} \inf_{R_{z}\in\mathbb{R}} \|R-R_{z}\|_{0,\Omega_{z}} \|v\|_{1,\omega_{z}} \\ &+ C_{22} \sum_{F\in\mathcal{F}} |F|^{1/4} \inf_{r_{F}\in\mathbb{R}} \|r-r_{F}\|_{0,F} \|v\|_{1,\Omega_{F}} \\ |B(u-\hat{u},v)| &\leq [C_{1}\|\varepsilon\|_{1} + C_{2} \operatorname{osc}(R,r)] \|v\|_{1} \\ &[\operatorname{osc}(R,r)]^{2} = \sum_{z\in\bar{\mathcal{V}}} D_{z}^{2} \inf_{R_{z}\in\mathbb{R}} \|R-R_{z}\|_{0,\Omega_{z}}^{2} + \sum_{F\in\mathcal{F}} |F|^{1/2} \inf_{r_{F}\in\mathbb{R}} \|r-r_{F}\|_{0,F}^{2} \end{split}$$



Reflecting on Effectivity Result and Analysis

 $K_0 \|\varepsilon\|_1 \le \|u - \hat{u}\|_1 \le K_1 \|\varepsilon\|_1 + K_2 \operatorname{osc}(R, r)$

- Argument style quite general
 - Different operators (eg. curl-curl), different elements (eg. Nédélec, Taylor-Hood)
 - Let form of residuals determine choice of error space \boldsymbol{W}
 - Higher regularity: higher order elements for V, then more vanishing moments for $v (\hat{v} + w)$
- Results hold under minimal practical assumptions (not an asymptotic or quasi-uniform analysis)
- Related notions of (data) oscillation in error analysis and AFEM convergence: Dörfler/Nochetto (2002), Nochetto/Siebert/Kreuzer/Cascon (2003,2008), Fierro/Veeser (2006), Bornemann/Erdmann/Kornhuber (1996)



Behavior of Face-Bump System

$$B_{FF'} = B(b_{F'}, b_F) \qquad D = diag(B)$$
$$\hat{B}_{FF'} = (b_{F'}, b_F)_{H^1(\Omega)} \qquad \hat{D} = diag(\hat{B})$$

- Argue that B and D are spectrally-equivalent
 - 1) Argue that B and \hat{B} are spectrally-equivalent, and D and \hat{D} are spectrally-equivalent
 - 2) Argue that \hat{B} and \hat{D} are spectrally-equivalent
- 1) If μ is an eigenvalue of B, then

 $m\lambda_{\min}(\hat{B}) \leq \mathsf{Re}(\mu) \leq M\lambda_{\max}(\hat{B})$ and $|\mathsf{Im}(\mu)| \leq M\lambda_{\max}(\hat{B})$

Argument for spectral equivalence of D and \hat{D} is even more trivial



Behavior of Face-Bump System

Spectral Equivalence of \hat{B} and \hat{D}

2) Let \hat{B}_T = element matrix for \hat{B} , \mathbf{v}_T = element coefficient vector for \mathbf{v}

$$\mathbf{v}^t \hat{B} \mathbf{v} = \sum_{T \in \mathcal{T}} \mathbf{v}_T^t \hat{B}_T \mathbf{v}_T$$

• If $k_0 \mathbf{v}_T^t \hat{D}_T \mathbf{v}_T \leq \mathbf{v}_T^t \hat{B}_T \mathbf{v}_T \leq k_1 \mathbf{v}_T^t \hat{D}_T \mathbf{v}_T$ for every T, then

$$k_0 \mathbf{v}^t \hat{D} \mathbf{v} \le \mathbf{v}^t \hat{B} \mathbf{v} \le k_1 \mathbf{v}^t \hat{D} \mathbf{v}$$

$$(\hat{B}_T)_{ij} = 2\frac{3!|T|}{7!} \begin{cases} \sum_{k=1}^4 d_k^{-2} & , \quad i=j \\ \frac{\cos\theta_{kl}}{d_k d_l} - \frac{2\cos\theta_{ij}}{d_i d_j} & , \quad i\neq j \end{cases} + \frac{3!|T|}{9!} \begin{cases} 8 & , \quad i=j \\ 4 & , \quad i\neq j \end{cases}$$

• Straight-forward analysis shows that \hat{B}_T is spectrally-equivalent to \hat{D}_T , and hence \hat{B} is spectrally-equivalent to \hat{D} . For piecewise linears, \hat{B}_T is NOT spectrally-equivalent to \hat{D}_T .



Illustrating the Above Assertions





Poisson Problem with (near) Singularity

Problem:

$$-\Delta u = f \text{ in } \Omega$$
 , $u = 0 \text{ on } \partial \Omega$, $u = \frac{\sin(\pi x)\sin(\pi y)\sin(\pi z)}{(0.001 + x^2 + y^2 + z^2)^{1.5}}$

Initial Mesh and an Adapted Mesh





Poisson Problem with (near) Singularity

Global and Local Effectivities: $\frac{\|\varepsilon\|}{\|u-\hat{u}\|}$, $\frac{\|\varepsilon\|_T}{\|u-\hat{u}\|_T}$ Compared with standard residual indicator

$$\eta^2 = \sum_{T \in \mathcal{T}} \eta_T^2 \quad , \quad \eta_T^2 = \frac{1}{2} \sum_{F \in \mathcal{F}_I} h_T \|r_F\|_{0,F}^2 + \sum_{F \in \partial T \cap \partial \Omega_N} h_T \|r_F\|_{0,F}^2 \; ,$$



Kentucky Applied and Computational Math Group



Poisson Problem with (near) Singularity

Error Convergence and Conditioning of Bump Matrix:



Preconditioning (symmetric, diagonal rescaling) necessary for adapted meshes



Discontinuous Diffusion Problem

Problem: $-a\Delta u = 0$ in $\Omega = (-1, 1)^3$

- $a = 10^5$ in $(0, 1)^3$, a = 1 elsewhere
- u = 1 at x = 1 and u = 0 at x = -1
- Homogeneous Neumann conditions on other four faces

An Adapted Mesh and a Look Inside





Discontinuous Diffusion Problem

Global Effectivities: $\frac{\|\varepsilon\|}{\|\bar{u} - \hat{u}\|}$ $\bar{u} \in V_{>3\times 10^6}$ $|||u - \hat{u}|||^{2} = |||u - \bar{u}|||^{2} + |||\bar{u} - \hat{u}|||^{2} = |||u - \bar{u}|||^{2} + (|||\bar{u}|||^{2} - |||\hat{u}|||^{2})$ Face-Bump Residual 4.5 4 3.5 Global Effectivity з 2.5 2



Kentucky Applied and Computational Math Group



Discontinuous Diffusion Problem

Error Convergence and Conditioning of Bump Matrix:





Problem:
$$-\epsilon \Delta u + u_x = 1$$
 in $\Omega = (0, 1)^3$, $u = x - \frac{e^{(x-1)/\epsilon} - e^{-1/\epsilon}}{1 - e^{-1/\epsilon}}$

- $\epsilon = 0.1$
- u = 0 at x = 0 and x = -1
- Homogeneous Neumann conditions on other four faces







Global and Local Effectivities: $\frac{\|\varepsilon\|_1}{\|u - \hat{u}\|_1}$, $\frac{\|\varepsilon\|_{1,T}}{\|u - \hat{u}\|_{1,T}}$







Error Convergence and Conditioning of Bump Matrix:





Global Effectivity and Error Convergence for $\epsilon = 10^{-2}$:





Another Convection-Diffusion Problem

Problem: $-\Delta u + \mathbf{b} \cdot \nabla u = 1$ in $\Omega = (-1, 1)^3$, u = 0 on $\partial \Omega$, where $\mathbf{b} = (-12y, 12x, 12z)$

Global Effectivity and Error Convergence





Anisotropic Diffusion Problem

Problem: $-\nabla \cdot (A\nabla u) = 1$ in $\Omega = (-1, 1)^3$

- $A = \operatorname{diag}(1, \epsilon, \epsilon^{-1})$, $\epsilon = 10^{-3}$
- Homogeneous Dirichlet conditions
- Error estimated as in Discontinuous-Diffusion problem

Global Effectivity and Error Convergence





Non-Linear Reaction-Diffusion Problem

Problem:
$$-\Delta u + e^u = f$$
 in $\Omega = (0, 1)^3$, $u = 0$ on $\partial \Omega$
 $u = (x^2 + y^2 + z^2 + 10^{-4})^{-3/2} \sin(\pi x) \sin(\pi y) \sin(\pi z)$

 $B(\hat{u} + \varepsilon, v) = F(v) - B(\hat{u}, v) \rightsquigarrow B(\hat{u}; \varepsilon, v) = F(v) - B(\hat{u}, v)$ for all $\varepsilon \in W$

Global Effectivity and Error Convergence



Kentucky Applied and Computational Math Group





Hope for Flexibility in $\mathbb{R}^3,$ Experience in \mathbb{R}^2





Measurements in Different Norms



Hessian Recovery in $W^{2,1}(\Omega)$, $|u|_{2,1} = \int_{\Omega} |u_{xx}| + 2|u_{xy}| + |u_{yy}| dV = 12$

NT	94	481	2031	8334	33704	135632
$ arepsilon _{2,1}$	7.8728	9.3262	10.282	10.992	11.496	11.798
EFF	0.6561	0.7772	0.8568	0.9160	0.9580	0.9832

Kentucky Applied and Computational Math Group



Eigenvalue Problems



- Grubisic/Ovall 2008, Bank/Grubisic Ovall 2010, error estimates, adaptivity, covergence acceleration
- Analysis needs approximate error function(s) in \mathcal{H}
 - Works for clusters of eigenvalues, degenerate (multiplicity> 1) eigenvalues, low-regularity eigenfunctions



Goal-Oriented Adaptivity

- Interested in driving down error in some (small) regions.
- Must be mindful of pollution effects.



- Ovall 2007, in a similar vein as Rannacher/Becker, Giles/Süli, etc.
- Some form of dualweighting of the residual