

Adaptive multigrid via subcycling on complementary grids

Tim Chartier

Department of Mathematics

University of  ashington

chartier@math.washington.edu





Collaborators

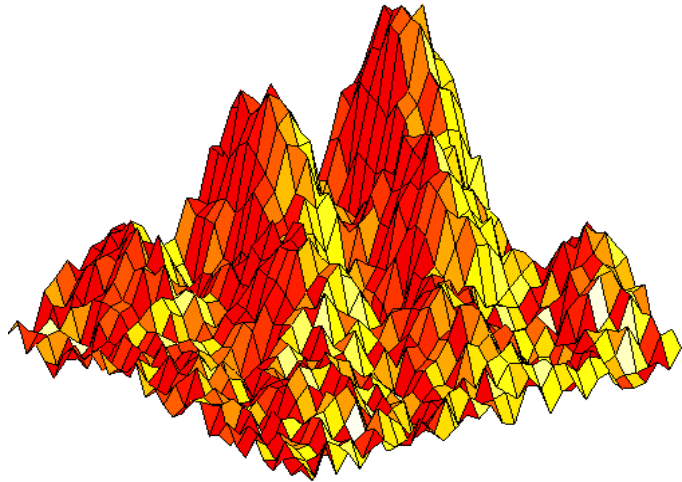


- This work was funded under a Research and Development grant at Lawrence Livermore National Lab.
- Primarily collaboration with Edmond Chow
- Thanks also extended to the following:
 - Steve McCormick
 - John Ruge
 - Tom Manteuffel
 - Marian Brezina
 - Rob Falgout

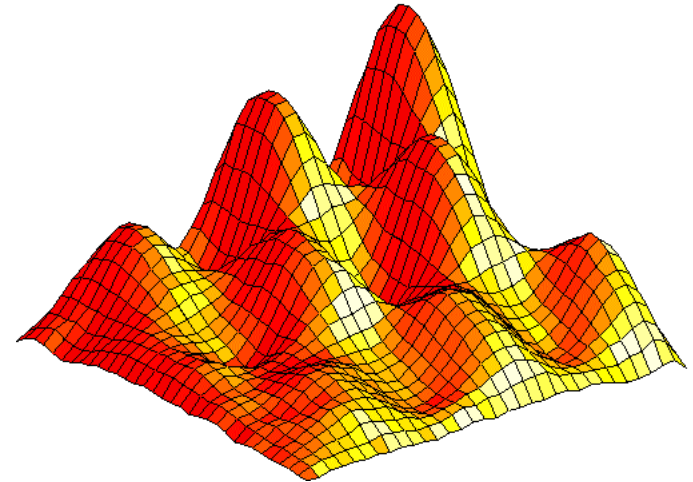


Multigrid cycle

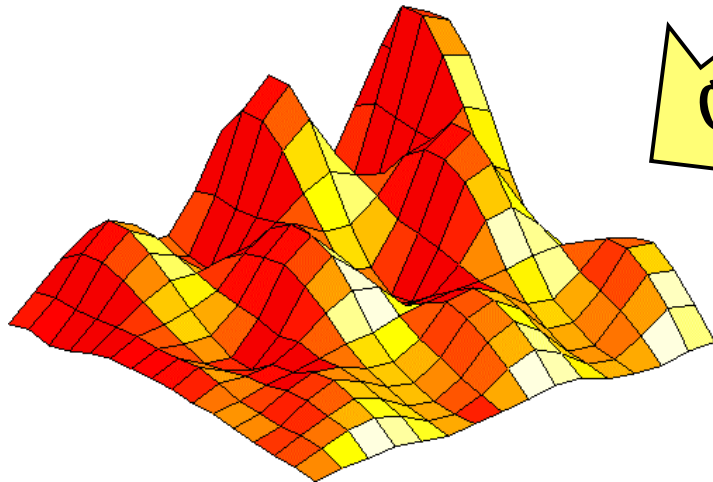
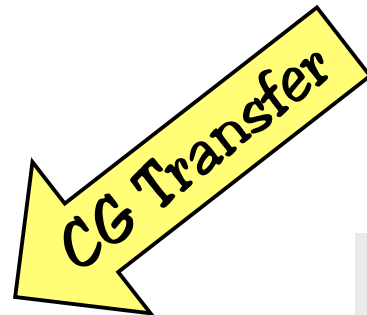
for **elliptic** problems



Initial Error on fine grid



Smoothed Error on fine grid



Smoothed Error on coarse grid

Error must be reduced by

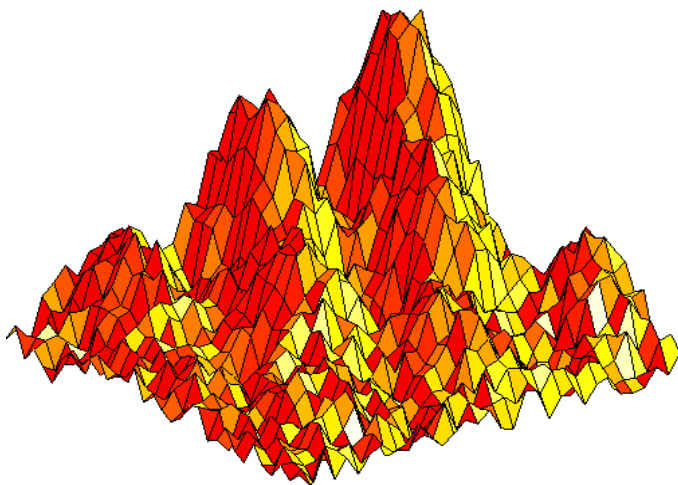
- relaxation
- coarse-grid correction



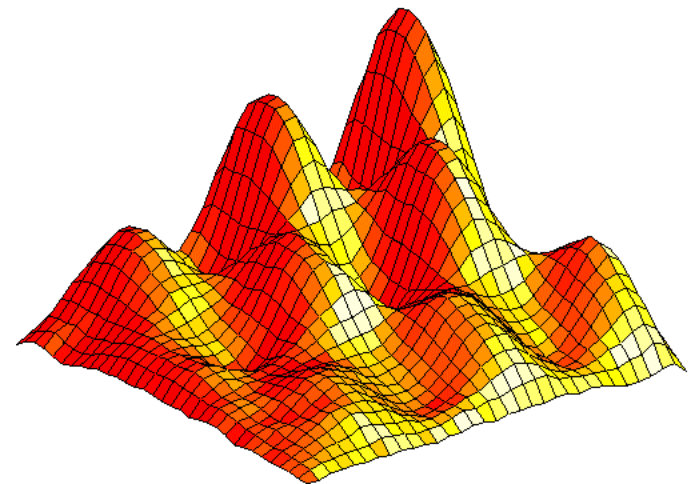
Smooth **error**

So, **relaxation** (Jacobi or Gauss-Siedel) produced geometrically smooth error for the PDE:

$$u_{xx} + u_{yy} = f$$



Initial Error

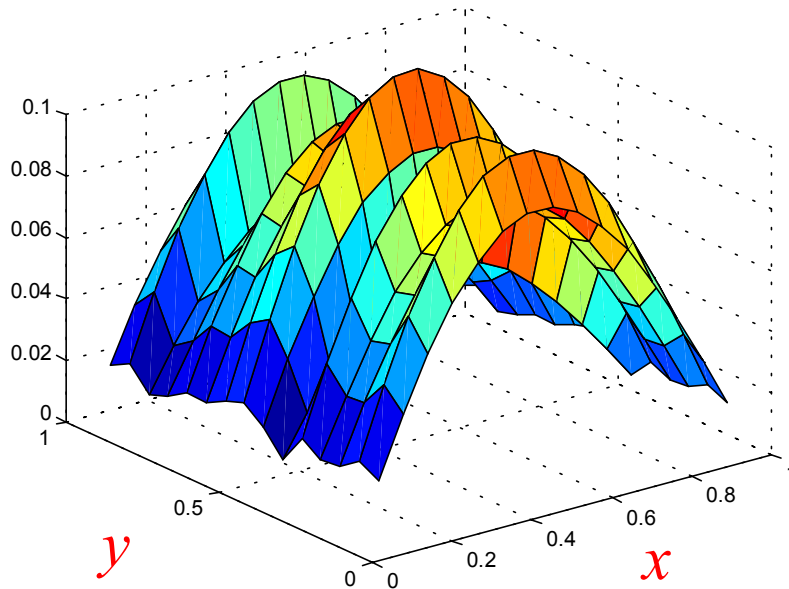


Smoothed Error



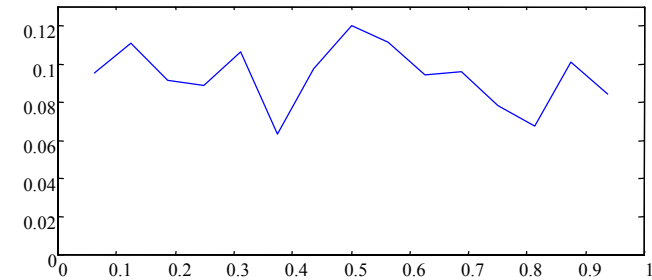
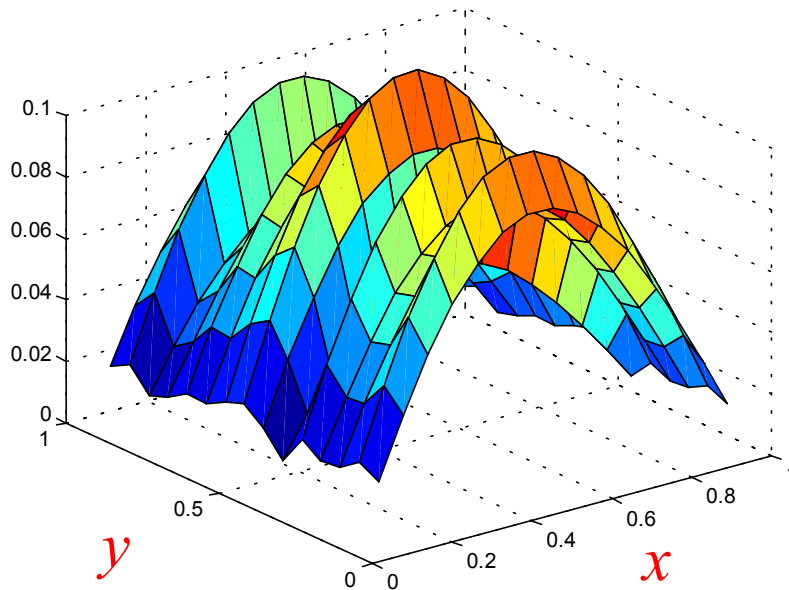
Algebraically smooth **error**

Consider $u_{xx} + (0.001) u_{yy} = f$. Then 50 sweeps of Gauss-Seidel produce the following error:

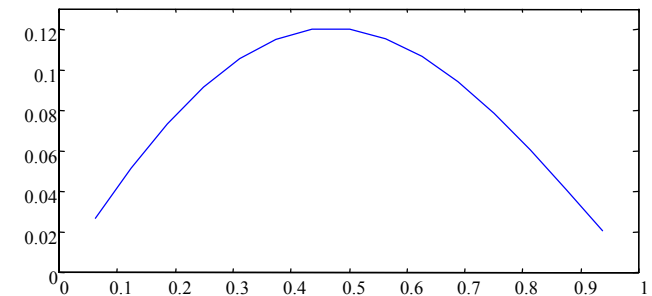


Algebraically smooth **error**

Another look at what it means to be smooth can be seen in the following observation:



Error along line of constant x



Error along line of constant y

Algebraically smooth error is not always geometrically smooth. Automatically choosing appropriate interpolation weights is a goal of algebraic methods.



Algebraically **smooth** error

Assume standard relaxation methods, such as Richardson.

$$\mathbf{u}_1 = \mathbf{u}_0 + \frac{\omega}{\|A\|_2} \mathbf{r}_0 \Rightarrow \mathbf{e}_1 = \left(I - \frac{\omega}{\lambda_n} A \right) \mathbf{e}_0$$

$$\text{If } A\mathbf{e}_0 = \lambda\mathbf{e}_0, \text{ then } \mathbf{e}_1 = \left(1 - \omega \frac{\lambda}{\lambda_n} \right) \mathbf{e}_0$$

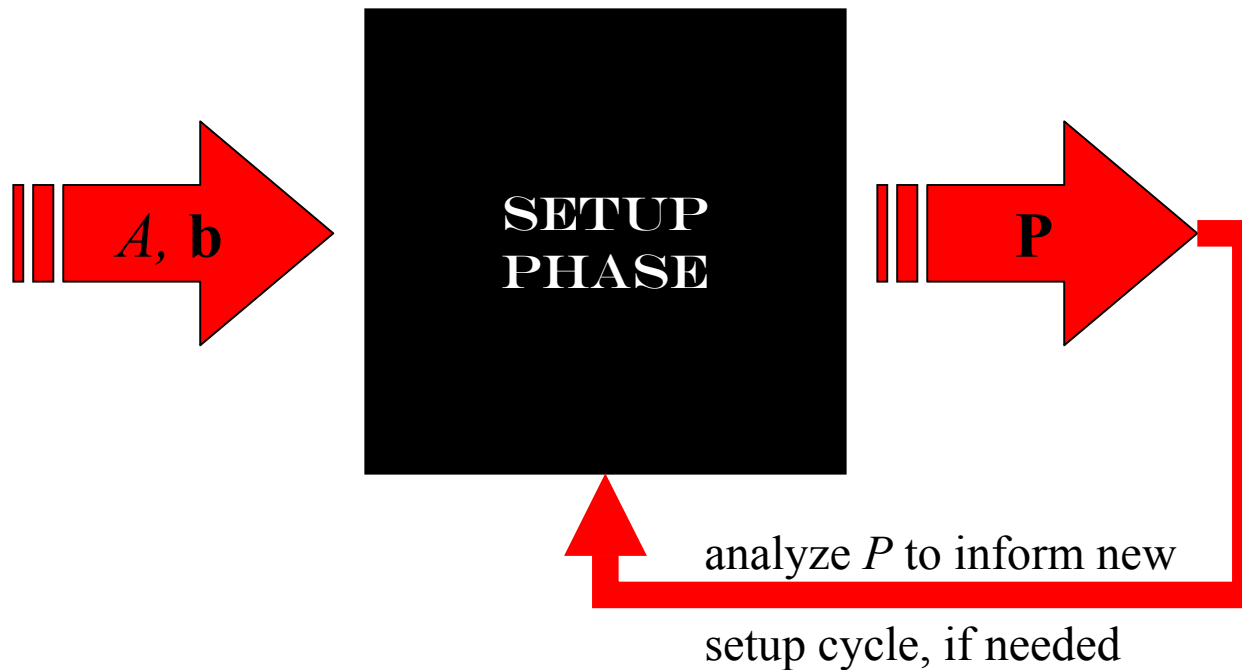
$$\text{If } \lambda \ll \lambda_n \Rightarrow \mathbf{e}_1 \approx \mathbf{e}_0$$

$$\lambda \approx \lambda_n \Rightarrow \text{factor} \approx 1 - \omega$$

Eigenvectors associated with small eigenvalues of A must be approx. by coarse-grid correction



Adaptive MG

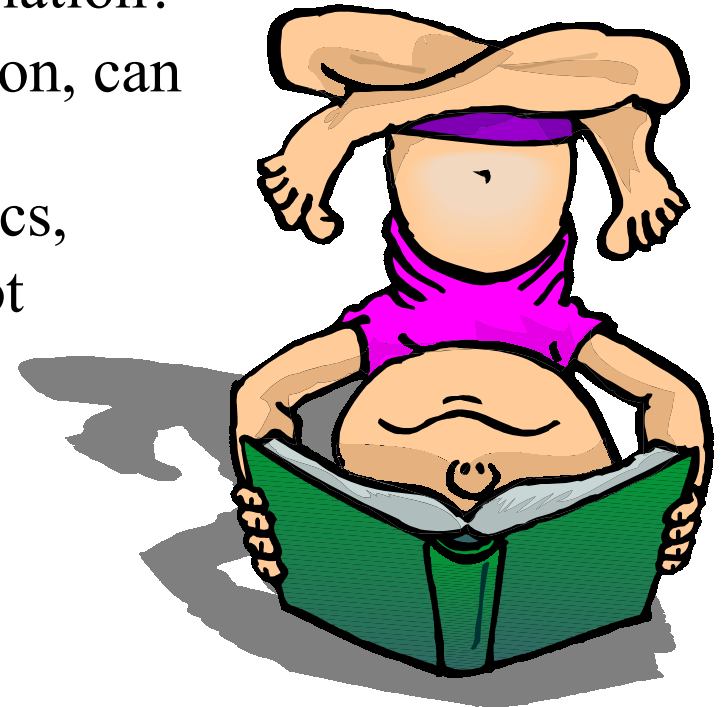


- Since relaxation is fixed, the goal of adaptive MG schemes is to choose an effective interpolation matrix P ($R = P^T$).
- If P appears ineffective, design an algebraic algorithm to improve prolongation.



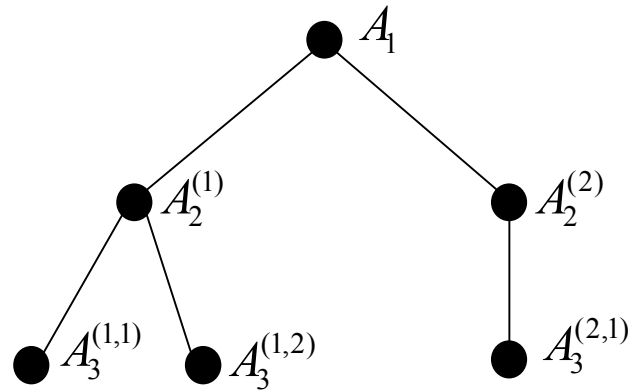
Improving **ineffective** interpolation

- If P is not effective, then interpolation is not approximating low mode(s).
- Can the method **self-improve** interpolation?
- Without doing a spectral decomposition, can we determine the “missed” modes?
- As indicated by the earlier mathematics, the method produces a error that is not captured by the method—a linear combination of the “missed” modes.



Subcycling on **complementary** grids

The subcycling takes the following form:



1. Relax $A_1 v_1 = 0$ with random initial guess. Use relaxed vector to form $P_1^{(1)}$ (and $A_2^{(1)}$).
2. Relax $A_2^{(1)} v_2 = 0$ with all-ones initial guess. Use relaxed vector to form $P_2^{(1,1)}$ (and $A_3^{(1,1)}$).

----- **Base cycle complete** -----

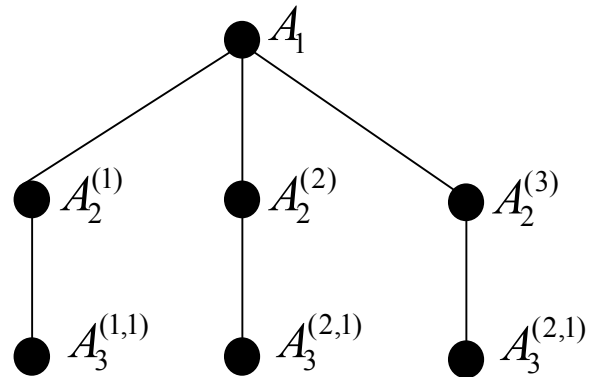
3. Test $A_2^{(1)} v_2 = 0$ (using random guess). If conv. slow (as in this e.g.), use relaxed vector to form $P_2^{(1,2)}$ (and $A_3^{(1,2)}$).

⋮



Subcycling on **complementary** grids

A cheaper variant of this scheme would take the form:

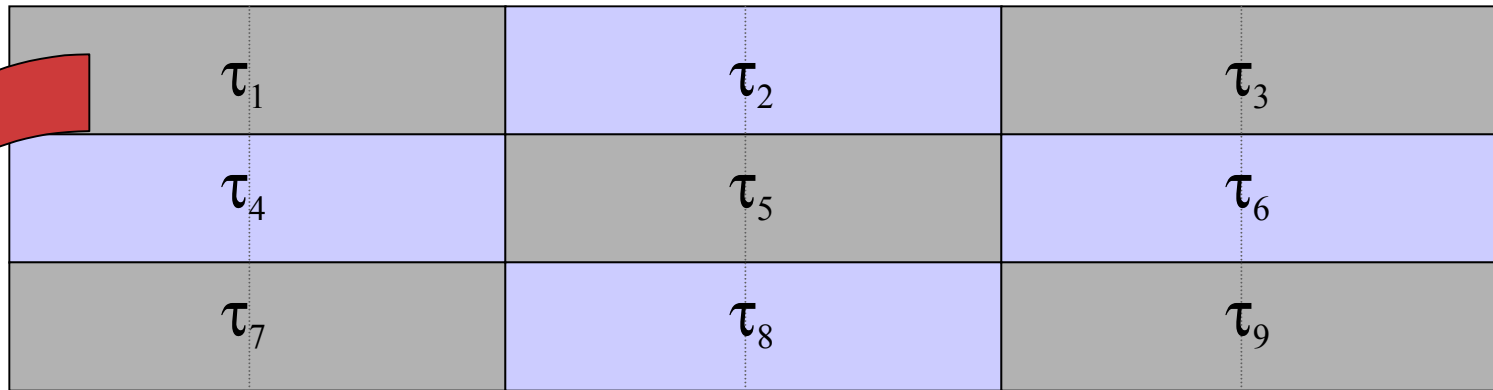


- This defines a general cycling (specifically subcycling).
- How is prolongation formed?



Spectral AMGe

Let \mathcal{A} be a partition of the space into agglomerates τ .



$$A_{\tau_1} V = VD$$

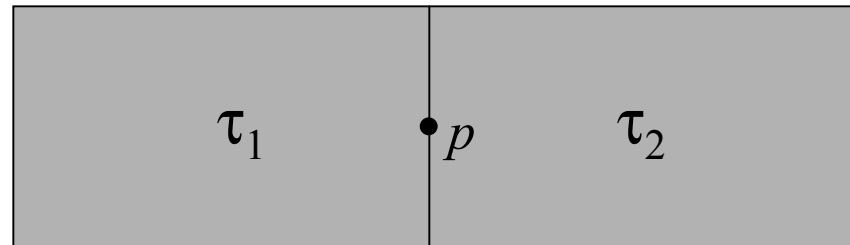
$$P_{\tau_1} = \begin{bmatrix} | & | & & | \\ v_1 & v_2 & \cdots & v_{m_\tau} \\ | & | & & | \end{bmatrix}$$

Idea: Use representative vectors from adaptive scheme.



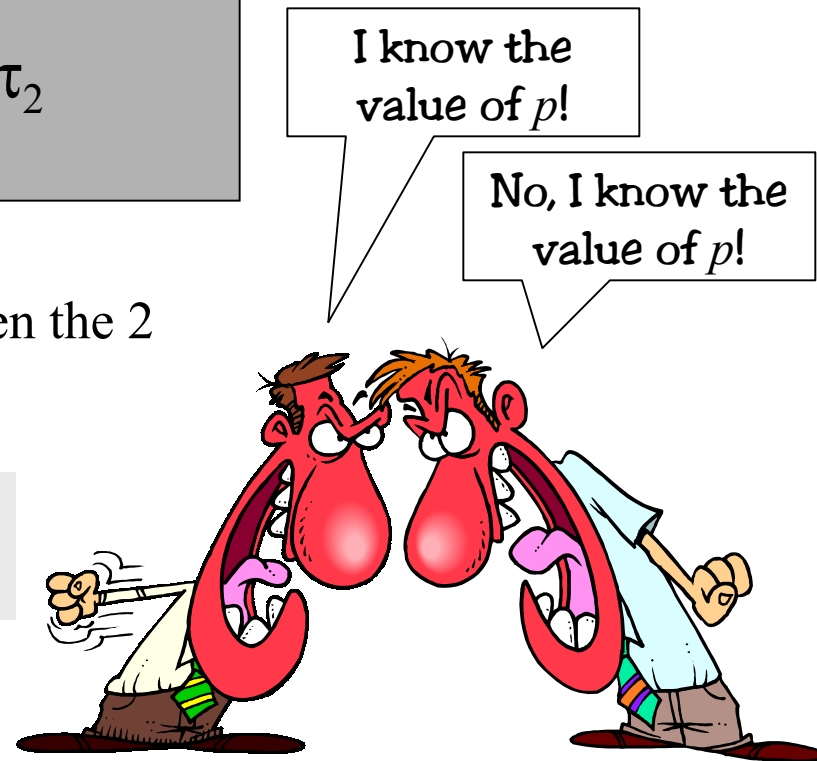
Forming the **global P**

What about $p \in \partial\tau$?



A **conflict** arises for the value of p between the 2 agglomerates

Let p be the average of the formulas determined in each of its agglomerates.



Forming the **global P**

Assume x is a global smooth vector.

For each $\tau \in \mathcal{A}$, form an intra-agglomerate interpolation vector p_τ as follows:

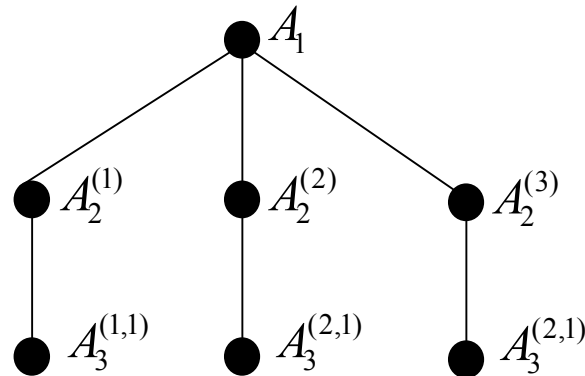
- Let x^τ be the restriction of x to agglomerate τ .
- For each dof i in τ that lies on the boundary of $n_i > 1$ agglomerates, let the i^{th} component of x^τ denoted x_i^τ equal x_i^τ / n_i
- Form p_τ by extending x^τ with zeros outside of τ .

The columns of the global interpolation operator P are the vectors p_τ for all $\tau \in \mathcal{A}$.



Numerical results

The following numerical experiments utilize the less costly subcycling scheme.



All problems will have Dirichlet boundary and utilize 4 x 4 agglomerates



Numerical results

34 x 34 Poisson problem square elements

k	Conv.	Subcycles	Grid Complexity	Operator Complexity
2	0.20	2	1.12	1.10
3	0.20	2	1.15	1.12
4	0.17	2	1.15	1.13

34 x 34 Poisson problem rectangle elements (5:1)

k	Conv.	Subcycles	Grid Complexity	Operator Complexity
2	0.22	6	1.35	1.31
3	0.27	6	1.44	1.37
4	0.25	7	1.54	1.45

Note: Same result if fine level linear equation is diagonally scaled.



Numerical results

34 x 34 rotated anisotropic diffusion; square elements, $\theta = 0^\circ$

k	Conv.	Subcycles	Grid Complexity	Operator Complexity
2	0.24	10	1.59	1.51
3	0.24	11	1.81	1.68
4	*	*	*	*

34 x 34 rotated anisotropic diffusion; square elements, $\theta = 30^\circ$

k	Conv.	Subcycles	Grid Complexity	Operator Complexity
2	0.22	7	1.41	1.36
3	0.24	7	1.51	1.43
4	0.21	8	1.62	1.51

34 x 34 rotated anisotropic diffusion; square elements, $\theta = 45^\circ$

k	Conv.	Subcycles	Grid Complexity	Operator Complexity
2	0.21	8	1.47	1.41
3	0.21	8	1.59	1.50
4	0.26	7	1.51	1.43



Current work

Current and future work includes:

- Continue multilevel testing on problems such as linear elasticity
- Compare efficiency with other adaptive methods
- Consider more costly subcycling scheme
- Combining information from each level

