

Energy Minimizing Algebraic Multigrid for Systems of Partial Differential Equations

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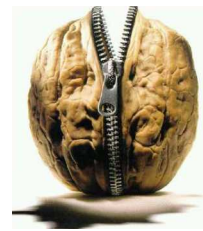
Sandia National Labs



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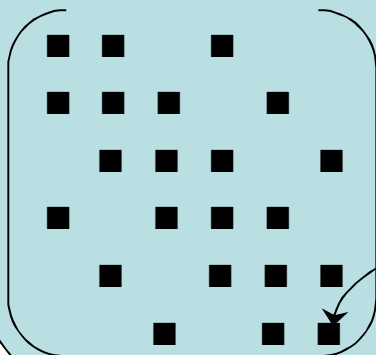
Project in a Nutshell



PDE systems

$$\begin{pmatrix} -\Delta & \nabla \\ \nabla \cdot & \end{pmatrix} \begin{pmatrix} u \\ p \end{pmatrix} = f$$

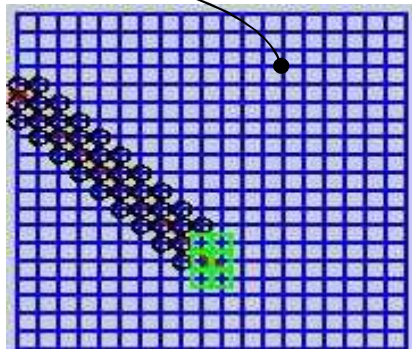
$$u = \sum_k u_k(x) \Psi_k(\omega)$$



$u = f$

$$A x = b$$

$$\begin{pmatrix} * & * & & \\ * & * & * & * \\ & * & * & \\ * & & * & \end{pmatrix} \begin{pmatrix} \rho \\ u \\ T \\ B \end{pmatrix} = f$$



Algebraic Multigrid

Energy Minimizing
prolongators

$$\text{KKT: } \begin{pmatrix} G & B^T \\ B & \end{pmatrix}$$

goals: flexibility &
robustness

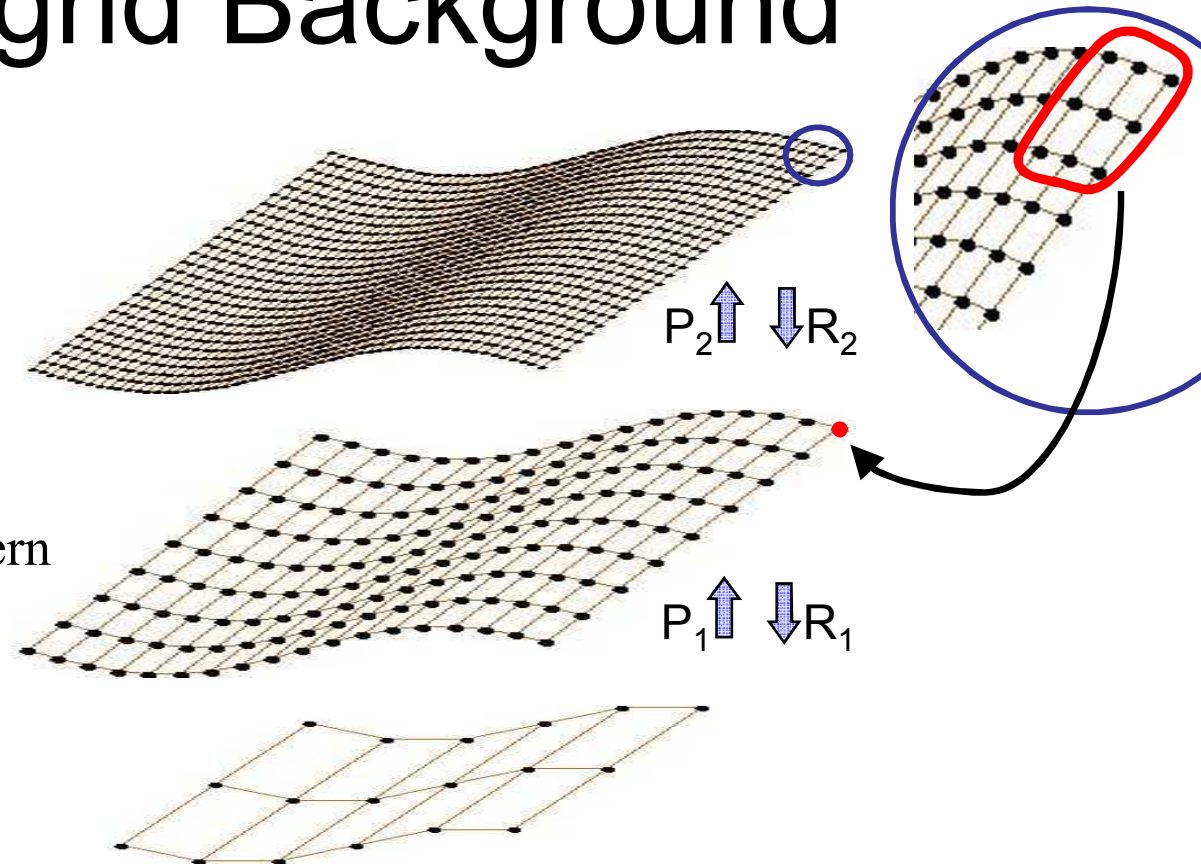
Constraints:
sparsity pattern
accurate modes
Smoothers



Algebraic Multigrid Background

Solve $A_3 u_3 = f_3$

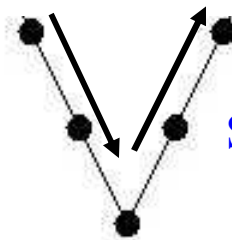
- Construct graph & coarsen
- Determine P_i & R_i sparsity pattern
- Determine P_i & R_i 's coefs
- Project: $A_i = R_i A_{i+1} P_i$



Smooth $A_3 u_3 = f_3$. Set $f_2 = R_2 r_3$.

Smooth $A_2 u_2 = f_2$. Set $f_1 = R_1 r_2$.

Solve $A_1 u_1 = f_1$ directly.



Set $u_3 = u_3 + P_2 u_2$.

Set $u_2 = u_2 + P_1 u_1$.

Brandt, McCormick,
Ruge, Stuben

Prior Accomplishments: Incompressible flow

$$A = \begin{bmatrix} F & \nabla \\ \nabla \cdot & 0 \end{bmatrix}, \quad M = \begin{bmatrix} F & \nabla \\ & -\hat{S} \end{bmatrix} \quad \& \quad S = \nabla \cdot F^{-1} \nabla$$

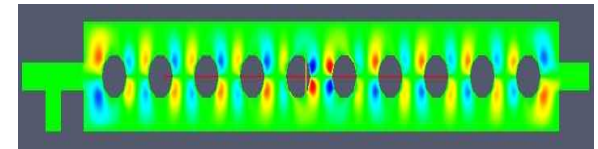
Murphy, Golub, Wathen

AMG $S \approx (\nabla \cdot \nabla) F_p^{-1} \Rightarrow \hat{S}^{-1} = F_p \Delta^{-1}$

Elman, Loghin, Kay, Silvester, Wathen '01-'03

- Algebraic $\hat{S}$
- $\hat{S}$ for stabilized A , $A_{2,2} \neq 0$
- New BC treatment in $\hat{S}$
- Integration in Sandia application codes

$$\min_{F_p} \|F_p \nabla - \nabla F\|$$



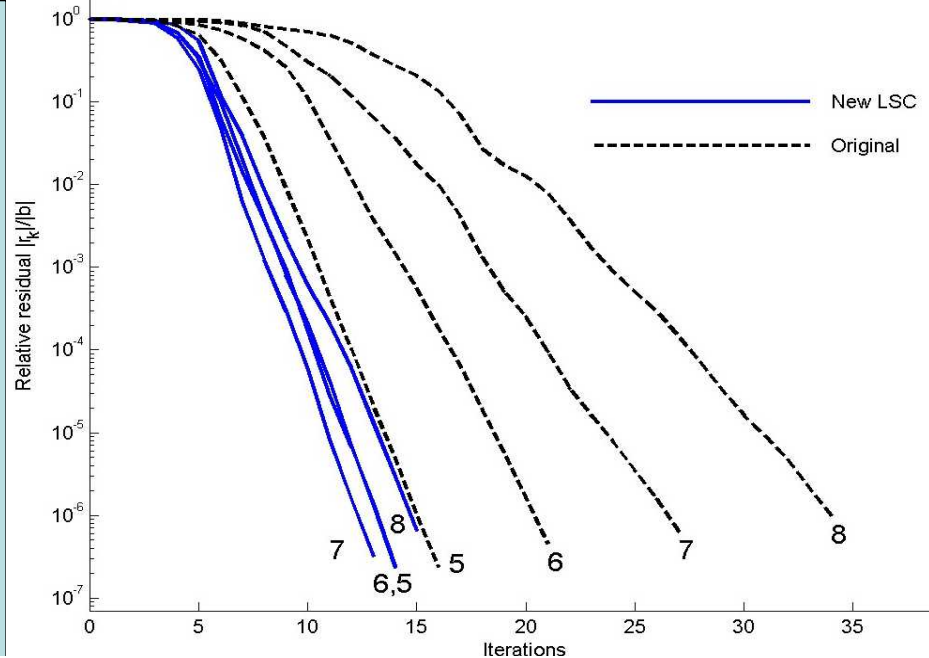
■ Smoothed Aggregation: new AMG method for $A \neq A^T$

- Low cost/iteration
- Accurate interpolation of difficult modes
- $P = (I - \Omega A) P_s$ $R = (P_s)^T (I - A \Theta)$
- Local minimization based on $A^T A$ norm

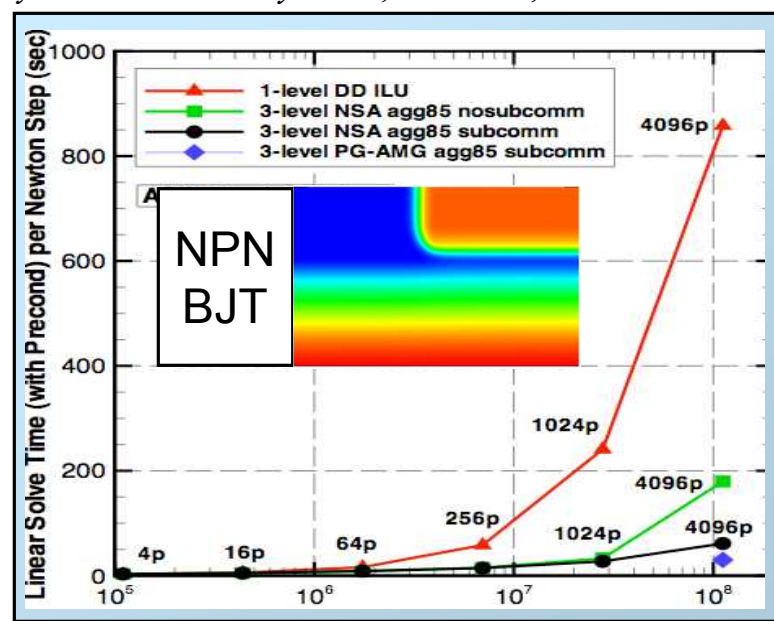
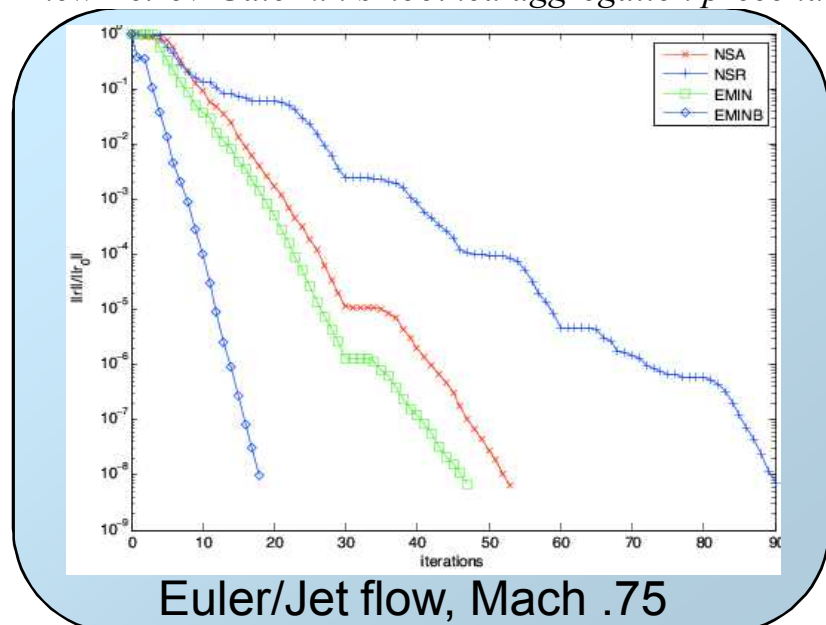
$R = ?$, $\omega = ?$
Minimize what?

⇒ New algorithm fairly robust & often gives mesh independent convergence

Q_1-P_0		Fp		S-LSC	
	$2^n \times 3 \cdot 2^n$	n=5	n=6	n=5	n=6
	Re 10	35	37	16	22
	Re 100	66	79	19	25
Q_1-Q_1	Re 200	92	100	26	27
	Re 10	32	35	19	26
	Re 100	61	76	19	28
	Re 200	84	93	22	29



- (1) *Least-squares preconditioners for stabilized ... Navier-Stokes Equations*, Elman, Howle, S, Silvester, T, SISC'07.
- (2) *A Taxonomy ... of Parallel Block Multilevel Preconditioners ...*, Elman, Howle, S, Shuttleworth, T, JCP'08.
- (3) *Boundary Conditions in Approximate Commutator Preconditioners ...*, Elman, T, submitted to ETNA.
- (4) *A new Petrov-Galerkin smoothed aggregation preconditioner for nonsymmetric linear systems*, Sala & T, SISC'08.



Prior Accomplishments: AMG & Maxwell

$$\nabla \times \nabla \times + \sigma$$

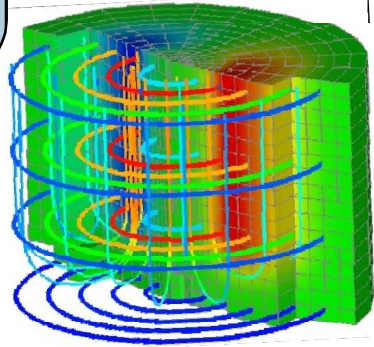
Small σ

$\Rightarrow$ large near null space

$\Rightarrow$ iterative solver problems

Ascher, Haber, Beck, Hiptmair, Xu,
Kolev, Pasciak, Vassilevski, SNL

**Exact Discrete
Reformulation**



$$\begin{pmatrix} \Delta_v^{(e)} & \sigma \nabla \\ \sigma \nabla \cdot & \Delta^{(n)} \end{pmatrix}$$

$\Rightarrow$ Laplacian dominated

New blk diagonal preconditioner

- standard AMG on (2,2)
- 1 special prolongator + standard AMG

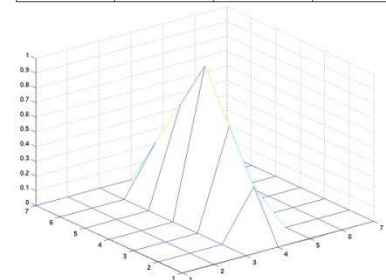
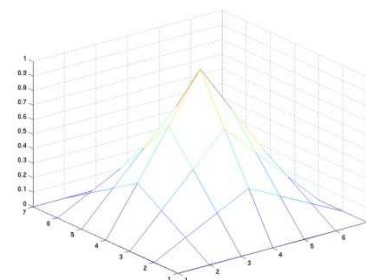
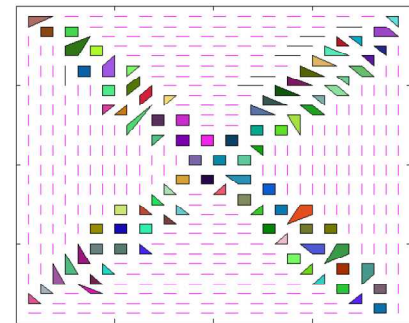
Irregular Coarsening

- detection

$$z_t = -Az + \delta_i \text{ with } z(0) = 0$$

$$\Rightarrow \begin{cases} z_t(\Delta t) \approx \Delta t A \delta_i + \delta_i \\ z(\infty) = A^{-1} \delta_i \end{cases}$$

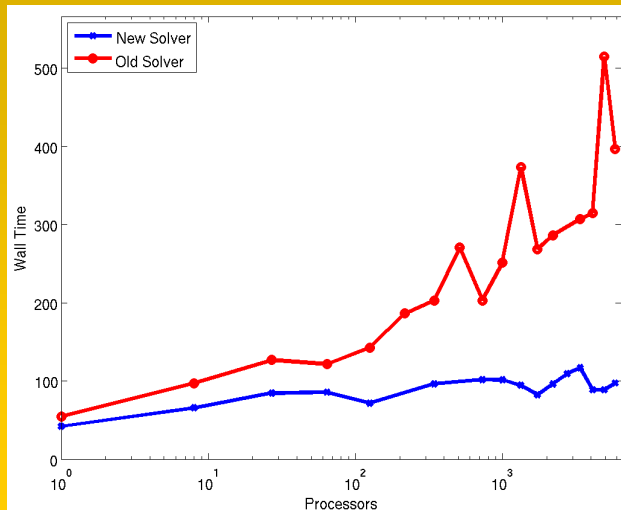
- prolongator basis functions



Brannick, Brezina, MacLachlan,
Mantueffel, McCormick

Prior Accomplishments: AMG & Maxwell

Red Storm Weak Scaling



Discrete formulation

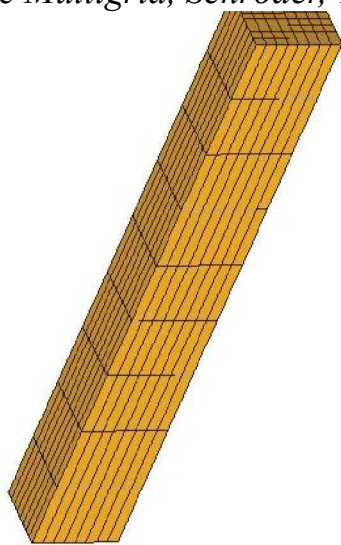
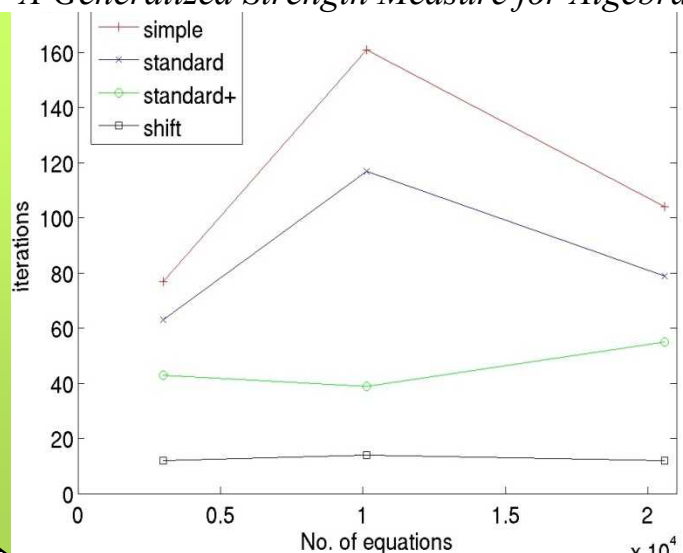
$$\begin{pmatrix} \Delta_v^{(e)} & \sigma \nabla \\ \sigma \nabla \cdot & \Delta^{(n)} \end{pmatrix}$$

⇒ Laplacian dominated

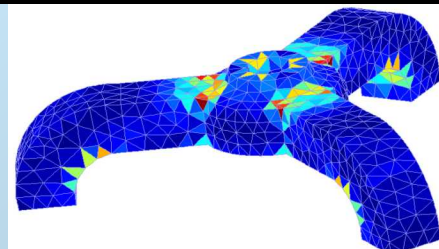
New blk diagonal preconditioner

- standard AMG on (2,2)
- 1 special prolongator + standard AMG

- (1) An AMG approach based on a compatible gauge reformulation of Maxwell's equations, Bochev, H, S & T, SISC'08.
- (2) Auxiliary AMG preconditioners for Mixed Finite Element Methods, T., J. Xu, Y. Zhu, submitted to DD'08.
- (3) A new smoothed aggregation multigrid method for anisotropic problems, Gee, H, T, NLAA, 09.
- (4) A Generalized Strength Measure for Algebraic Multigrid, Schroder, T, Olson, submitted to NLAA.



≈DOFs	Coefs	ODE
2k	33	13
14k	67	13
110k	129	18





A Massively Parallel Algebraic Multigrid Solver

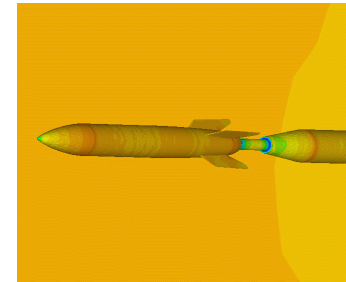
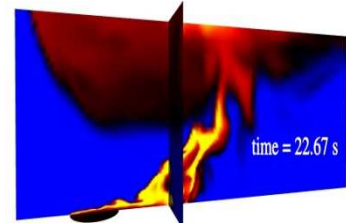


Smoothed Aggregation Capabilities

- Limited variable dofs/block support
- Aggregation with arbitrary coarsening, load balancing, ...

Variety of Smoothers

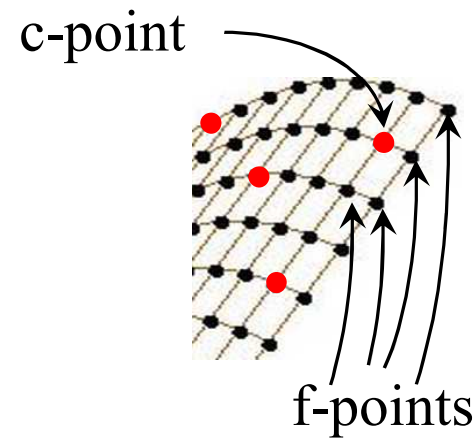
Leverages Trilinos, PETSc, SuperLU, kLU, ParMETIS, ...



Smoothed Aggregation Advantages/Disadvantages

- + mesh independent convergence on many problems
- + ability to emphasize accurate interpolation of important modes
- + relatively inexpensive cost per iteration and setup cost
- Constructing P 's coefficients $\Rightarrow$ very modest control over P 's sparsity pattern
 $\Rightarrow$ rigid rules followed during coarsening/aggregation
- Accurate interpolation of special modes requires widening P

Prolongation & Minimization: $\|P\|_A$



Consider

$$\begin{pmatrix} A_{ff} & A_{fc} \\ A_{cf} & A_{cc} \end{pmatrix} \begin{pmatrix} u_f \\ u_c \end{pmatrix} = \begin{pmatrix} b_f \\ b_c \end{pmatrix}$$

Then

$$\underbrace{\begin{pmatrix} I_f & 0 \\ R_f & I_c \end{pmatrix} \begin{pmatrix} A_{ff} & A_{fc} \\ A_{cf} & A_{cc} \end{pmatrix} \begin{pmatrix} I_f & P_f \\ 0 & I_c \end{pmatrix}}_{\begin{pmatrix} A_{ff} & E_{fc} \\ E_{cf} & A_H \end{pmatrix}} \begin{pmatrix} y_f \\ y_c \end{pmatrix} = \begin{pmatrix} b_f \\ Rb \end{pmatrix}$$

$$\begin{pmatrix} A_{ff} & E_{fc} \\ E_{cf} & A_H \end{pmatrix}$$

$\Leftrightarrow$ 2 level AMG with $(A_{ff})^{-1}$ as relaxation

$$P = \begin{pmatrix} P_f \\ I_c \end{pmatrix}, \quad R = \begin{pmatrix} R_f & I_c \end{pmatrix}$$

$$A_H = RAP$$

$\Rightarrow$ want $E_{fc} = (A_{ff} \ A_{fc})P$ & $E_{cf} = R \begin{pmatrix} A_{ff} \\ A_{cf} \end{pmatrix}$ to be small

$\Rightarrow$ want A_{ff} to be well-conditioned

Brandt, Brannick, Livne,
Falgout, Zikatinov

Ideal $P_f = -A_{ff}^{-1} A_{fc} \Rightarrow$ perhaps use to guide sparsity pattern of P_f

Difficult to do some of these things in smoothed aggregation

Energy Minimizing Prolongators

$$\min_{\bar{P}} \sum_i \|p_i\|_A^2 \quad \text{subject to} \quad B \begin{pmatrix} p_1 \\ \vdots \\ p_m \end{pmatrix} = g, \quad P = [p_1 \ p_2 \ \cdots \ p_m]$$

B : accurate interpolation of important modes, e.g. $P \text{ const} = \text{const}$

$$\Rightarrow \begin{pmatrix} A & & & & \\ & A & & & \\ & & A & & \\ & & & A & \\ & B & & & \lambda \end{pmatrix} \begin{pmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \\ \lambda \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ g \end{pmatrix}$$

Constraints improve conditioning!

$$BB^T = \begin{pmatrix} * & * & * & & & \\ * & * & * & & & \\ * & * & * & & & \\ & & & \ddots & & \\ & & & & * & * & * \\ & & & & * & * & * \\ & & & & * & * & * \end{pmatrix}$$

1) Solve via CG & enforce constraints each iteration:

$$Q \hat{A} Q^T p = rhs \quad Q = I - B^T(B B^T)^{-1}B$$

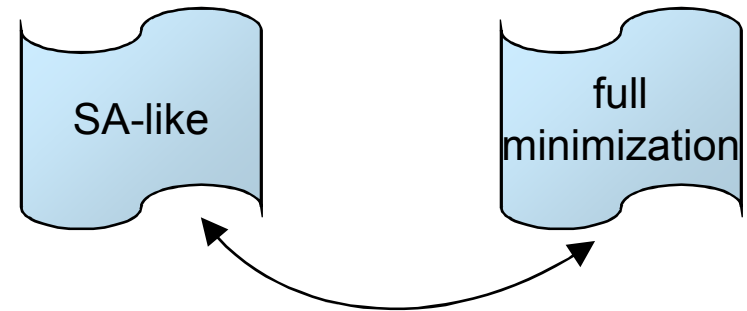
Mandel, Brezina, Vanek,
Brannick, Zikatanov, Wan

2) Each iteration ...

- a) AP
- b) Remove nonzeros that extend beyond desired sparsity pattern
- c) Apply projection

Research Issues

- Cost of P's construction
 - smoothed aggregation connection
 - selective iteration
 - Amortize multiple linear systems
 - ⇒ Criteria for acceptable columns of P



- Prolongator sparsity patterns
 - easy to consider irregular sparsity patterns
 - application driven vs. $P_f = -A_{ff}^{-1} A_{fc}$
 - widening P & linear independence

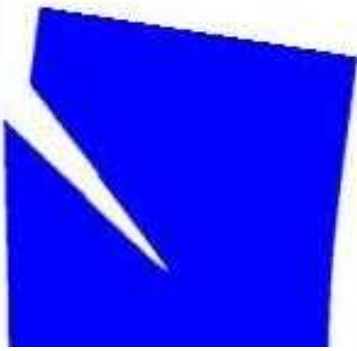
- Nonsymmetric
 - Perhaps GMRES on

$$Q \hat{A} Q \gg P \ll = 0 \quad Q = I - B^T (B B^T)^{-1} B$$

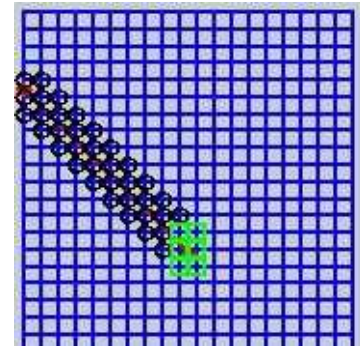
$$Q \hat{A}^T Q \gg R \ll = 0$$
 - Norms/scaling for minimization

- Additional constraints
 - application driven vs. adaptive AMG

Brezina, Falgout,
MacLachlan, Manteuffel,
McCormick, Ruge,
Sanders



XFEM & AMG



$$u(x) = \sum_i \phi_i(x) u_i + \sum_i \phi_i(x) H(x) z_i + \dots, \quad H(x) = \begin{cases} 1 & \varphi \geq 0 \\ 0 & \varphi < 0 \end{cases}, \quad \Gamma = \{(x, y) \mid \varphi(x, y) = 0\}$$

How to interpolate to special degrees of freedom?

XFEM philosophy would probably coarsen normally
but have coarse special functions embedded in A_H

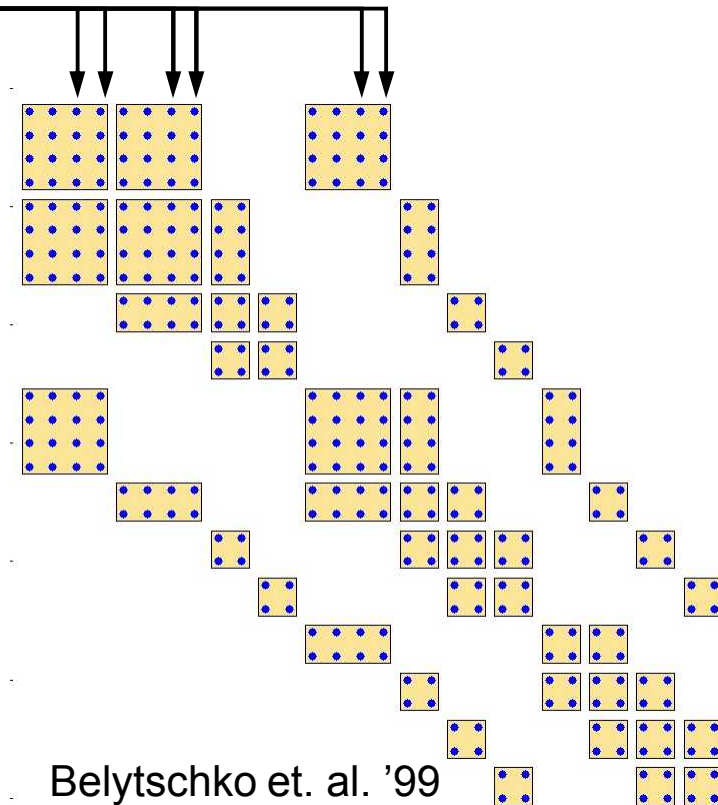
Could project level set information to coarse grids?

sparsity pattern

- coarse special DOFs interpolate only to fine special DOFS
- restrict basis function support to one side of discontinuity

special constraints?

- enforce accurate interpolation of Heaviside function?



Belytschko et. al. '99

MHD

$$\mathbf{R}_m = \frac{\partial(\rho \mathbf{v})}{\partial t} + \nabla \cdot [\rho \mathbf{v} \otimes \mathbf{v} - \mathbf{T}] - \boxed{\mathbf{J} \times \mathbf{B}} = \mathbf{0}; \quad \mathbf{T} = -\left(P + \frac{2}{3}\mu(\nabla \cdot \mathbf{u})\right) \mathbf{I} + \mu[\nabla \mathbf{u} + \nabla \mathbf{u}^T]$$

$$R_p = \frac{\partial(\rho)}{\partial t} + \nabla \cdot [\rho \mathbf{v}] = 0$$

$$R_e = \frac{\partial(\rho e)}{\partial t} + \nabla \cdot [\rho \mathbf{v} e + \mathbf{q}] - \mathbf{T} : \nabla \mathbf{v} - \boxed{\eta \|\mathbf{J}\|^2} + Q^{rad} + Q = 0$$

$$\mathbf{R}_B = \frac{\partial \mathbf{B}}{\partial t} + \nabla \times \mathbf{E} = \mathbf{0} \quad \mathbf{J} = \frac{1}{\mu_0} \nabla \times \mathbf{B} \quad \mathbf{E} = -\mathbf{v} \times \mathbf{B} + \eta \mathbf{J} + \underbrace{\frac{1}{en}(\mathbf{J} \times \mathbf{B} - \nabla p_e)}_{\text{Hall}}$$

Ion Momentum Diffusion $10^{-7} \rightarrow 10^{-3}$

Magnetic Flux Diffusion $10^{-7} \rightarrow 10^{-3}$

Ion Momentum Advection $10^{-4} \rightarrow 10^{-2}$

Alfven Wave $10^{-4} \rightarrow 10^{-2}$

Whistler Wave $10^{-7} \rightarrow 10^{-1}$

Magnetic Island Sloshing 10^0

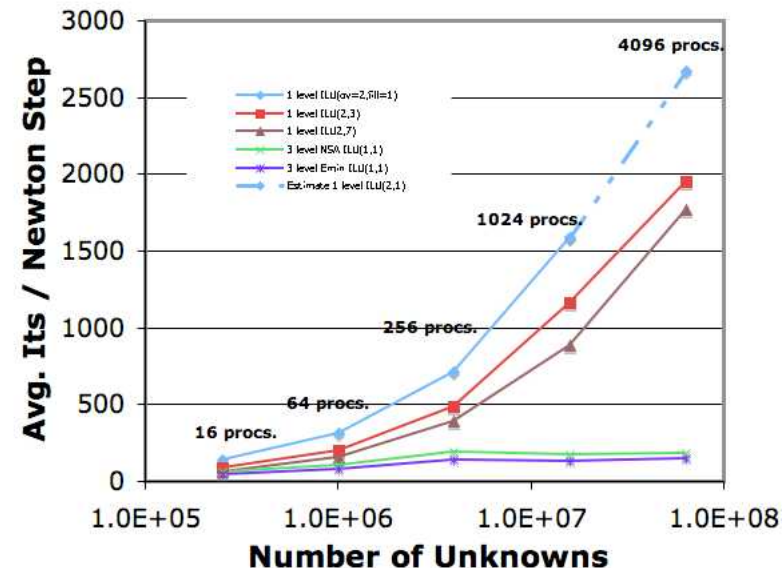
Magnetic Island Merging 10^1

⇒ Strongly Coupled, Multiple Time- and Length-Scale, Nonlinear, Nonsymmetric System with Parabolic and Hyperbolic Character

Steady-state Resistive MHD

- 1+ Billion unknowns
- 6000 cores Cray XT3/4
- Newton-GMRES/ML 4 level
- 18 Newton steps
- 223 Avg. Linear Its./ Newton step
- 84 min. for solution

Weak Scaling Study: Resistive MHD VP Formulation (2D MHD Pump)



MHD & AMG

- Explore better *minimization* prolongators
- Possibly new constraints based on analysis

$$\begin{pmatrix} * & * & & \\ * & * & * & * \\ & * & * & \\ * & & * & \end{pmatrix} \begin{pmatrix} \rho \\ u \\ T \\ B \end{pmatrix} = f$$

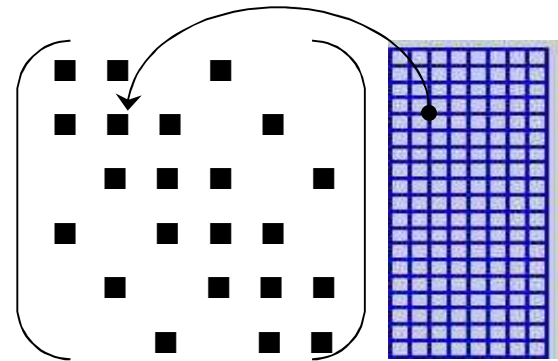
Use

$$\begin{pmatrix} F & \\ & \hat{S} \end{pmatrix} \quad \text{or} \quad \begin{pmatrix} F & B^T \\ B & \hat{S} \end{pmatrix}$$

- $\Rightarrow$ generate hierarchy
- $\Rightarrow$ generate prolongators

- Grid/spatially based block smoothers

Pernice, Tocci,
Chacon, Knoll



- F/C choice via compatible relaxation-like
- Sparsity pattern choice via A_{ff} iteration
- Schur complement-based smoothers

$$\begin{pmatrix} u \\ p \end{pmatrix} \leftarrow \begin{pmatrix} u \\ p \end{pmatrix} + \omega \begin{pmatrix} F & B^T \\ B & \hat{S} \end{pmatrix}^{-1} r$$

Stochastic PDEs

$$u = \sum_k u_k(x) \Psi_k(\omega)$$

$$\lambda = \sum_k \lambda_k(x) \Psi_k(\omega)$$

$$M_{ijk} = \int \Psi_i \Psi_j \Psi_k d\mu$$

$$-\sum_j [\sum_k M_{ijk} \lambda_k(x) [u_j(x)]_x]_x = f_i$$

Different diffusion coefficients $\Rightarrow$ different features, e.g. $\sum_k M_{ijk} \lambda_k$:

Gaussian variables $\Rightarrow$ potential loss of SPD

spatial coarsening

$$M = \begin{pmatrix} M_{11} & & \\ & M_{22} & \\ & & M_{33} \end{pmatrix} \quad P = \begin{pmatrix} P_1 & & \\ & P_2 & \\ & & P_3 \end{pmatrix} \quad P = \begin{pmatrix} P_1 & \cdot & \cdot \\ \cdot & P_2 & \cdot \\ \cdot & \cdot & P_3 \end{pmatrix}$$

Nonintrusive $\longrightarrow$ Intrusive

$$[A_H]_{ij} = P_i A_{ij} P_j, \quad P_i \leftarrow \text{AMG}(A_{ii})$$

- Stochastic coarsening (or spectral coarsening)
 - Interplay with spatial coarsening
 - Special constraints when nearly non-spd?

- *Drop* higher order terms or leave choice to energy minimization

Elman, Furnival, Powell,
LeMaire, Knio,
Debusschere, Najm,
Ghanem

Summary

- Energy minimizing framework (Tuminaro,Hu)
 - Sparsity patterns
 - Family of methods with varying costs
 - Nonsymmetric
 - Multiple constraints
- XFEM with Waisman(Columbia) & within SNL applications (Tuminaro)
 - Broaden variable block capability
 - Coarse level sets & additional constraints
 - Sparsity patterns
- MHD with Shadid(SNL)/Chacon(Oakridge) (Tuminaro,Cyr,Hu)
 - Schur complements & smoothers
 - Special constraints to address difficult modes
- Stochastic PDEs with Phipps/Najm(SNL), Elman(Maryland) (Tuminaro)
 - Stochastic coarsening
 - Special constraints as system approaches non-SPD

Application areas are important ... but research is applicable to a broader class of difficult problems