

# NON-GALERKIN COARSE GRIDS FOR ALGEBRAIC MULTIGRID

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## Abstract.

Algebraic multigrid (AMG) is a popular and effective solver for systems of linear equations that arise from discretized partial differential equations. While AMG has been effectively implemented on large scale parallel machines, challenges remain, especially when moving to exascale. In particular, stencil sizes (the number of nonzeros in a row) tend to increase further down in the coarse grid hierarchy and this growth leads to more communication. Thus, as problem size increases and the number of levels in the hierarchy grows, the overall efficiency of the parallel AMG method decreases, sometimes dramatically. This growth in stencil size is due to the standard Galerkin coarse grid operator,  $P^T AP$ , where  $P$  is the prolongation (i.e., interpolation) operator. For example, the coarse grid stencil size for a simple 3D 7-point finite differencing approximation to diffusion can increase into the thousands on present day machines, causing an associated increase in communication costs. We therefore consider algebraically truncating coarse grid stencils to obtain a non-Galerkin coarse grid. First, the sparsity pattern of the non-Galerkin coarse grid is determined by employing a heuristic minimal “safe” pattern together with strength-of-connection ideas. Second, the nonzero entries are determined by collapsing the stencils in the Galerkin operator using traditional AMG techniques. The result is a reduction in coarse grid stencil size, overall operator complexity, and parallel AMG solve phase times.

**Key words.** multigrid, algebraic multigrid, non-Galerkin coarse grid, parallel computing, high-performance computing

**AMS subject classifications.** 65F08, 65N55

**1. Introduction.** The goal of this paper is to introduce a non-Galerkin coarse grid strategy that improves the parallel performance of algebraic multigrid (AMG) [6, 14]. AMG is of interest because it is a popular and effective solver of large sparse linear systems in parallel, by virtue of being *scalable* or *optimal* and solving a linear system with  $n$  unknowns with only  $O(n)$  work. Consider solving the linear system

$$A\mathbf{x} = \mathbf{b}, \tag{1.1}$$

where  $\mathbf{x}, \mathbf{b} \in \mathbb{R}^n$ . For the problems considered here,  $A \in \mathbb{R}^{n \times n}$  is assumed to be a symmetric and positive definite (SPD) matrix.

There are two main components to a multigrid method: the *smoother* (or *relaxation* method) and the *coarse grid correction* step. The coarse grid correction step involves operators that transfer information between the fine and coarse “grids”, denoted more generally by the space  $\mathbb{R}^n$  and the lower dimensional (coarse) vector space  $\mathbb{R}^{n_c}$ . We focus on classical Ruge-Stüben style AMG (RS-AMG) [14], which constructs the coarse space using a disjoint  $F/C$  splitting of the fine grid unknowns, with the  $C$ -points forming the coarse grid. We let  $P : \mathbb{R}^{n_c} \rightarrow \mathbb{R}^n$  be the *interpolation* (or *prolongation*) operator, and generally the *restriction* operator is taken to be  $P^T$ . Optimality is achieved when smoothing and coarse grid correction are complementary. In the classical setting of scalar elliptic problems, this means that the smoother is a simple iterative algorithm like Gauss-Seidel, which is effective at reducing high frequency error. The remaining low frequency error is then accurately represented and efficiently eliminated on coarser grids via the coarse grid correction step. As a result, all error frequencies are uniformly damped with a linear cost. The two-grid multigrid method for solving (1.1) is then defined in Algorithm 1. In practice, we use a multilevel method to solve (1.1) by recursively applying Algorithm 1 to the correction step in line 5. The proposed work considers replacing the Galerkin coarse grid operator  $P^T AP$  with a sparser approximation  $A_c$ , which maintains the AMG convergence rate, but improves parallel efficiency.

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**Algorithm 1:** Twogrid( $A, \mathbf{x}, \mathbf{b}$ )

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1	<b>Input:</b> $A$	{Matrix}
2	$x$	{Initial guess to linear system}
3	$b$	{Right-hand-side vector}
4	Relax $\nu_1$ times on $A\mathbf{x} = \mathbf{b}$	
5	Correct $\mathbf{x} \leftarrow \mathbf{x} + P(P^TAP)^{-1}P^T(\mathbf{b} - A\mathbf{x})$	
6	Relax $\nu_2$ times on $A\mathbf{x} = \mathbf{b}$	
7	<b>return</b> $x$	

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Controlling the sparsity pattern of  $P^TAP$  is important because AMG (including the target BoomerAMG package in *hypre*) produces coarse grids with a maximum coarse grid stencil size that grows with problem size. This is problematic in parallel, because as stencil size increases on coarser levels, standard matrix partitioning couples processors that were not coupled on previous, finer levels. Thus, the communication pattern also grows as problem size increases, with the risk that for exascale problems, the maximum coarse grid stencil size may produce unscalable communication patterns. This increase in communication is well documented [16, 8]. In particular, the work [8] describes how even the best current practices in *hypre* still result in a sharp increase in number of messages and in overall communication cost when moving to coarse grids. For example, the model diffusion problem considered in [8] resulted in a growth from 6 MPI sends on the finest level to 245 MPI sends on the worst coarse grid for a machine with 65K cores. The result was that the time spent on some coarse levels in the hierarchy, despite being much smaller in terms of number of nonzeros and number of unknowns, was actually larger than the time spent on the finest level.

The need to improve coarse grid sparsity has been a main driver for research-based improvements to *hypre*. Classical parallel AMG (i.e., classical modified interpolation and Falgout coarsening [9]) is indeed a useful and powerful method, but at large numbers of cores, the communication cost ruins what is otherwise a computationally optimal method. As an example, consider Figure 1.1, where the time to solution for classical parallel AMG is plotted for the simple 3D 7-point finite difference diffusion operator. A weak scaling study is done with 25,000 unknowns per core on an Intel cluster with a fast InfiniBand QDR interconnect, and the time grows dramatically with core count. This result led to the important developments of aggressive coarsening [16] and extended interpolation [15], which lead in this experiment to a reduction in coarse grid stencil size from the thousands to the hundreds. The resulting time to solution is also commensurately reduced, in large part due to reduced communication, as indicated by the “Best practices AMG”<sup>1</sup> plot in Figure 1.1. However, even with these advancements, the time to solution is still growing in the figure, leaving us room for improvement through communication reducing strategies.

Our strategy is to further reduce the communication costs by replacing  $P^TAP$  with a sparser approximation. While we focus on a purely algebraic approach, non-Galerkin methods have already been explored in settings where geometric information is used to aid the method [2, 20] in choosing sparsity patterns and matrix coefficients. This previous work already indicates that a significant reduction in coarse grid stencil size is possible without a serious reduction in multigrid convergence. The work [5] discusses, but does not experiment with, a purely algebraic non-Galerkin coarse grid approach that computes each coarse grid matrix row based on minimizing a quadratic functional. While this is an intriguing approach, it has the goal of directly computing coarse grid equations (i.e., coarse grid matrix rows) without the use of  $P$ . This is a significantly more difficult and expensive proposition than the proposed approach. Our goal is simpler because we continue to use  $P$  to define a Galerkin coarse grid and then sparsify this coarse grid to derive a more efficient multigrid scheme.

<sup>1</sup>For a complete discussion of the *hypre* parameters used for “Best practices AMG” and “Classical parallel AMG”, see Section 5.3.

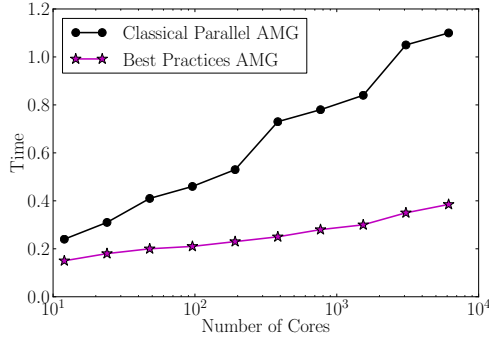


Fig. 1.1: AMG weak scaling as motivation: parallel timings for classical parallel AMG and current best practices for a simple model diffusion problem.

More recent work [17] has followed a similar path to ours in sparsifying coarse grid Galerkin operators for smoothed aggregation (SA) [19], and while not fully developed or tested in parallel, shows much promise.

Our overall strategy is to begin with an existing AMG method, and to remove entries from the Galerkin operator each time a new level in the hierarchy is formed. Thus our goal is to have sparser coarse grid operators than given by Galerkin coarse grids and to also maintain AMG convergence when compared to the corresponding Galerkin coarse grid method. The algorithm consists of two phases. The first phase chooses a sparsity pattern for the new coarse grid operator, and the second phase removes or “collapses” entries in  $P^T A P$  that lie outside of that sparsity pattern. While we focus on the BoomerAMG package in *hypre*, we believe that the approach is general enough to be applicable to most AMG codes. To this end, we have also implemented the proposed method in a SA setting (see Section 5.2).

In Section 2, we first provide a mathematical motivation for our approach. In Section 3, we state the resulting algorithm. In Section 4, we describe a near optimal non-Galerkin coarse grid operator, and compare our method to the near optimal method for model diffusion problems. In Section 5, we give serial results for a variety of diffusion and elasticity problems, followed by parallel results for diffusion problems.

**2. Mathematical Motivation.** In this section, we provide the mathematical motivation for our approach. Assume that an AMG method is applied to an SPD matrix,  $A$ . During construction of an AMG hierarchy, the Galerkin coarse grid,  $A_g = P^T A P$ , has been computed, but the rows contain too many nonzeros, or the number of nonzeros per row is growing too quickly. Our goal is to replace  $A_g$  with a sparser approximation,  $A_c$ , that is spectrally equivalent in the sense that

$$\exists \alpha, \beta \in \mathbb{R}^+ \text{ such that } \alpha \leq \lambda(A_c^{-1} A_g) \leq \beta, \quad (2.1)$$

with  $\alpha$  and  $\beta$  both close to 1. Alternatively, we show in Theorem 2.1 that minimizing

$$\theta \equiv \|I - A_c A_g^{-1}\|_2 \quad (2.2)$$

is a sufficient heuristic for defining  $A_c$  to produce an effective AMG method or preconditioner.

Building on results in [11], define the symmetric two-grid error propagator for AMG as

$$E_K = (I - M^{-T} A)^\nu (I - P K^{-1} P^T A) (I - M^{-1} A)^\nu, \quad (2.3)$$

where  $K$  is the coarse grid matrix and  $M$  defines the relaxation method (e.g., the diagonal of  $A$  in the case of Jacobi). Let  $E_{TG}$  denote the error propagator for the standard Galerkin

case,  $K = A_g$ , and let  $E_{PTG}$  denote the propagator for the *perturbed* two-grid case,  $K = A_c$ . Next, define preconditioners  $B_{TG}$  and  $B_{PTG}$  induced by the equations

$$E_{TG} = I - B_{TG}^{-1}A, \quad (2.4a)$$

$$E_{PTG} = I - B_{PTG}^{-1}A. \quad (2.4b)$$

We now relate the spectral radius  $\rho(E_{PTG})$  of the perturbed method to that of the Galerkin method. Similarly, we bound the condition number  $\kappa(B_{PTG}^{-1}A)$  in terms of  $\kappa(B_{TG}^{-1}A)$ .

**THEOREM 2.1.** *Define  $E_{TG}$ ,  $E_{PTG}$ ,  $B_{TG}$ ,  $B_{PTG}$ , and  $\theta$  as above, and assume that  $A_g$  and  $A_c$  are SPD. If  $\theta < 1$ , then*

$$\kappa(B_{PTG}^{-1}A) \leq \left( \frac{1+\theta}{1-\theta} \right) \kappa(B_{TG}^{-1}A) \quad (2.5)$$

and

$$\rho(E_{PTG}) \leq \max \left( \lambda_{\max}(B_{TG}^{-1}A) \cdot \frac{1}{1-\theta} - 1, 1 - \lambda_{\min}(B_{TG}^{-1}A) \cdot \frac{1}{1+\theta} \right). \quad (2.6)$$

*Proof.* Using a result from [11], we have that

$$\begin{aligned} \lambda_{\max}(B_{PTG}^{-1}A) &\leq \lambda_{\max}(B_{TG}^{-1}A) \cdot \max(\lambda_{\max}(A_c^{-1}A_g), 1) \\ &= \lambda_{\max}(B_{TG}^{-1}A) \cdot \frac{1}{\min(\lambda_{\min}(A_g^{-1}A_c), 1)}, \end{aligned} \quad (2.7)$$

and similarly

$$\lambda_{\min}(B_{PTG}^{-1}A) \geq \lambda_{\min}(B_{TG}^{-1}A) \cdot \frac{1}{\max(\lambda_{\max}(A_g^{-1}A_c), 1)}. \quad (2.8)$$

Since  $A_g$  and  $A_c$  are SPD, we have that

$$\begin{aligned} \rho(I - A_g^{-1}A_c) &= \max(\lambda_{\max}(A_g^{-1}A_c) - 1, 1 - \lambda_{\min}(A_g^{-1}A_c)) \\ &\leq \|I - A_g^{-1}A_c\|_2 = \|I - A_cA_g^{-1}\|_2 = \theta. \end{aligned}$$

Hence,  $\lambda_{\max}(A_g^{-1}A_c) \leq 1 + \theta$ ,  $\lambda_{\min}(A_g^{-1}A_c) \geq 1 - \theta$ , and (2.5) follows from (2.7) and (2.8). Since  $A$  and  $B_{PTG}$  are SPD, (2.6) follows from the additional fact that

$$\rho(E_{PTG}) = \max(\lambda_{\max}(B_{PTG}^{-1}A) - 1, 1 - \lambda_{\min}(B_{PTG}^{-1}A)).$$

□

**2.1. Heuristics.** In this section, we further motivate the algorithm heuristics based on Theorem 2.1. Our basic goal is to construct an operator  $A_c$  with a given sparsity pattern such that  $\theta$  is small. To state this more rigorously, we first introduce some notation. Define a *matrix nonzero pattern* (or *sparsity pattern*) as a set of tuples  $\{(i, j)\}$  and denote the space of matrices with given sparsity pattern  $\mathcal{N}$  by

$$\mathcal{N} \equiv \{A \in \mathbb{R}^{n \times n} : a_{ij} \neq 0 \text{ only if } (i, j) \in \mathcal{N}\}. \quad (2.9)$$

Similarly, define a *vector nonzero pattern* as a set of indices  $\{i\}$  and denote the space of vectors with given nonzero pattern  $\mathcal{I}$  by

$$\mathcal{I} \equiv \{\mathbf{x} \in \mathbb{R}^n : x_j \neq 0 \text{ only if } j \in \mathcal{I}\}. \quad (2.10)$$

Let  $\mathcal{N}_c$  and  $\mathcal{N}_g$  represent the sparsity patterns of  $A_c$  and  $A_g$ , respectively. Then, our aim is to define  $\mathcal{N}_c \subseteq \mathcal{N}_g$  and  $A_c \in \mathcal{N}_c$  such that  $\theta$  is small. We begin by stating  $A_c$  as a perturbation of  $A_g$ , i.e., let  $A_c \in \mathcal{N}_c$ ,  $A_g \in \mathcal{N}_g$ , and

$$A_c = A_g + E, \quad (2.11a)$$

$$\|I - A_cA_g^{-1}\|_2 = \|EA_g^{-1}\|_2 = \theta. \quad (2.11b)$$

Next, we develop heuristics for (2.11b) intended to reduce  $\theta$ . First, we develop a heuristic for “mid-range” or high energy modes,  $\mathbf{x}$ ,

$$A_g \mathbf{x} = \lambda \mathbf{x}, \quad (2.12a)$$

where  $\|\mathbf{x}\|_2 = 1$  and  $\lambda$  is not small, say  $\lambda \in [\rho(A_g)/10, \rho(A_g)]$ . Our simple row-wise heuristic uses Gershgorin rings by enforcing

$$\|\mathbf{e}_i\|_1 \leq \gamma \|\mathbf{a}_i^g\|_1, \quad (2.12b)$$

where  $(\mathbf{e}_i)^T$  and  $(\mathbf{a}_i^g)^T$  represent the  $i$ th row of  $E$  and  $A_g$ , and  $\gamma \in [0, 1]$ . Thus letting  $\max_i \|\mathbf{a}_i^g\|_1 = k\rho(A_g)$ , we have

$$\rho(E) \leq \gamma \max_i \|\mathbf{a}_i^g\|_1 \quad (2.12c)$$

$$\rho(E) \leq k\gamma \rho(A_g). \quad (2.12d)$$

Last for the mode  $\mathbf{x}$  in question, we can say

$$\|EA_g^{-1}\mathbf{x}\|_2 = \frac{1}{\lambda} \|E\mathbf{x}\|_2 \leq \frac{\rho(E)}{\lambda} \leq k\gamma \frac{\rho(A_g)}{\lambda}. \quad (2.12e)$$

For typical AMG problems from standard discretizations of the Poisson operator,  $k$  is small, usually in the vicinity of 2 or 3. Thus for mid-range or high energy modes, the impact on  $\theta$  from equation (2.12e) is minimal for the  $\gamma$  chosen here, which are on the order 0.01.

Much of the preceding argumentation for mid-range to high-energy modes centers around global eigenvalues, but it is important that the heuristic (2.12b) is row-wise. This locality implies that enforcing (2.12b) for a specific  $\gamma$  targets the locally mid-range to high energy modes, which may or may not correspond to the global mid-range to high energy modes.

The other case concerns  $\mathbf{x}$  as a low energy eigenmode such that  $\|\mathbf{x}\|_2 = 1$ , but  $A_g \mathbf{x} \approx \mathbf{0}$ . Then,  $\theta$  is small when

$$E\mathbf{x} \approx \mathbf{0} \quad \text{if} \quad A_g \mathbf{x} \approx \mathbf{0}. \quad (2.13a)$$

Since AMG typically makes a priori assumptions about the local behavior of the near null space, we can leverage that here as well to target (2.13a) as a heuristic. In particular, we enforce accuracy for a set of vectors,  $B$ , that represent the near null space, i.e.,

$$A_c B = A_g B \quad \Leftrightarrow \quad EB = \mathbf{0}. \quad (2.13b)$$

The standard choice for  $B$  is the constant, but could also be problem dependent, e.g., the rigid-body modes for elasticity. For the most common case of  $B = \mathbf{1}$ , we guarantee (2.13b) with classical AMG inspired stencil collapsing to remove the unwanted entries in  $A_g$ , so that  $E\mathbf{1} = \mathbf{0}$ . Classical stencil collapsing was originally developed for constructing interpolation operators and is well-known to be accurate for near null space modes. However, AMG interpolation techniques do not explicitly address accuracy for higher energy modes, thus necessitating heuristic (2.12b). When  $B$  contains multiple vectors, a generalized collapsing strategy is used, which we detail later in Section 3.3.1.

While this approach is based on the above heuristics, it should be noted that much of the successful classical AMG framework, e.g., strength-of-connection and interpolation formulas, is based on similar heuristic assumptions. Put another way, if the constant does not adequately represent a low energy vector  $\mathbf{x}$  locally, then the classical AMG framework in which we operate will already be problematic.

**3. Algorithm.** In this section, we first describe our algorithm for finding a suitable sparsity pattern  $\mathcal{N}_c$  for  $A_c$ . Second, we describe the algorithm for eliminating entries in  $A_g$  based on  $\mathcal{N}_c$  for the case of classical AMG scalar problems. The strategy is based on classical AMG stencil collapsing. Third, we discuss one possible generalization of our algorithm to

other PDEs, such as linearized elasticity, where the near null space of the matrix contains more than the constant vector.

The heuristics in Section 2 guide our algorithmic choices. The process of finding the sparsity pattern utilizes a drop tolerance that guarantees satisfaction of equation (2.12b), which is the heuristic targeting accuracy in  $A_c$  for mid-range to high energy modes. The process of stencil collapsing to eliminate entries is then done in such a way to target the second heuristic (2.13b) and give  $A_c$  accuracy for the important near null space modes.

**3.1. Choosing the Sparsity Pattern.** The goal of the sparsity pattern choice is to ensure an adequate nonzero pattern for spectral equivalence between  $A_g$  and  $A_c$ . We approach this problem in a two phase manner. The first phase initializes the sparsity pattern using the matrix graph of  $P$  and the fine grid operator  $A$  to target sufficient connections in  $A_c$  to approximate the Galerkin matrix stencil. The second phase guarantees heuristic (2.12b) to more directly target spectral equivalence for mid-range to high energy modes.

**Minimal Sparsity Pattern.** Considering the first phase, we must at a minimum choose coarse grid sparsity patterns that *allow* for reproducing a good approximation to the Galerkin matrix stencil. A central difficulty is the fact that it is not known how to define a sufficient minimal sparsity pattern on the coarse grid for a scalable AMG method. Because of this fact, our minimal sparsity pattern relies on heuristics.

We begin by noting that non-Galerkin strategies regularly succeed for geometric multigrid and result in bounded stencil growth. In contrast for algebraic multigrid, stencils typically grow because distance three (or farther) connections on the fine grid become distance-one connections on the coarse grid. To target eliminating these coarse grid connections that correspond to longer distance fine grid connections, we choose

$$\hat{\mathcal{N}}_c = \{(i, j) \text{ such that } (P_I^T A P + P^T A P_I)_{ij} \neq 0\} \quad (3.1)$$

as the minimal sparsity pattern, where  $P_I$  refers to injection between the coarse and fine grids. Typically  $P$  will have a connectivity pattern based on  $A$ , so it is easy to see that  $P_I A P$  will only connect distance one and two fine grid unknowns on the coarse grid. This results in a sparsity pattern similar to those achieved by geometric multigrid schemes.

This initial pattern allows for important matrix entries in  $A_g$  with a small magnitude to be preserved on coarse grids in  $\hat{\mathcal{N}}_c$ . These entries would normally be dropped if the classical strength-of-connection measure (which is based on magnitude) were used to compute  $\hat{\mathcal{N}}_c$ . Instead equation (3.1) uses the information (often of a geometric nature) present in the matrix graph of  $A$  to maintain connections on the coarse grid between all fine grid distance one  $C$ -point connections and some fine grid distance two  $C$ -point connections. (This assumes that classical RS-AMG type interpolation and coarsening schemes are used.) So while we will later use a collapsing scheme based on RS-AMG strength-of-connection and interpolation to eliminate entries in  $A_g$ , the concept of strength-of-connection is not sufficient by itself to construct  $\mathcal{N}_c$ . We note that [17] uses a similar approach in a SA setting to obtain a sparsity pattern.

To illustrate this issue, consider a simple example of grid-aligned anisotropic diffusion,  $-u_{xx} - \epsilon u_{yy} = f$ , discretized with the standard five-point finite-difference stencil given by  $A$  in (3.2a) below. The stencil for  $A_g$  in (3.2a) is that yielded by one level of semi-coarsening (coarsening in the  $x$ -direction only) as obtained with RS-AMG. The stencil for  $A_c$  in (3.2b) is a discretization of the problem on the coarse grid and provides a suitable non-Galerkin coarse grid for  $A_g$ . However, if the connections in the direction of weak diffusion are dropped in  $A_c$  to yield  $\tilde{A}_c$ , the spectral equivalence bounds are  $h$ -dependent. Hence, the value of  $\theta$  in

Theorem 2.1 approaches one, and we cannot guarantee an  $h$ -independent two-grid method.

$$A := \begin{bmatrix} & -\epsilon & \\ -1 & (2 + 2\epsilon) & -1 \\ & -\epsilon & \end{bmatrix}, \quad A_g := \begin{bmatrix} -\frac{\epsilon}{4} & -\frac{3}{2}\epsilon & -\frac{\epsilon}{4} \\ -\frac{1}{2} + \frac{\epsilon}{2} & (1 + 3\epsilon) & -\frac{1}{2} + \frac{\epsilon}{2} \\ -\frac{\epsilon}{4} & -\frac{3}{2}\epsilon & -\frac{\epsilon}{4} \end{bmatrix}, \quad (3.2a)$$

$$A_c := \begin{bmatrix} & -2\epsilon & \\ -\frac{1}{2} & (1 + 4\epsilon) & -\frac{1}{2} \\ & -2\epsilon & \end{bmatrix}, \quad \tilde{A}_c := \begin{bmatrix} & 0 & \\ -\frac{1}{2} & 1 & -\frac{1}{2} \\ & 0 & \end{bmatrix}, \quad (3.2b)$$

To see this  $h$ -dependence, we do a simple derivation using the well known [7] eigenvectors  $v_i$  and eigenvalues  $\lambda_i$  of the classic second-order finite-difference operator with stencil  $[-1 \ 2 \ -1]$ . Letting this 1D stencil be defined on a grid with  $n$  points, the corresponding eigenvalues and eigenvectors of  $A_c$  defined on an  $n \times n$  grid are given by

$$\lambda_{ij} = \frac{1}{2}\lambda_i + 2\epsilon\lambda_j, \quad v_{ij} = v_i \otimes v_j, \quad (3.3a)$$

where the indexing  $i, j < n$ . The spectrum of  $\tilde{A}_c$  can similarly be expressed with

$$\tilde{A}_c v_{ij} = \frac{1}{2}\lambda_i v_{ij}. \quad (3.3b)$$

Using this knowledge of the spectra, we have

$$\lambda(\tilde{A}_c^{-1} A_c) = \frac{\frac{1}{2}\lambda_i + 2\epsilon\lambda_j}{\frac{1}{2}\lambda_i} = 1 + 4\epsilon\lambda_i^{-1}\lambda_j. \quad (3.3c)$$

Hence,

$$1 \leq \lambda(\tilde{A}_c^{-1} A_c) \lesssim 1 + 4\epsilon \left( \frac{4-h}{h} \right). \quad (3.3d)$$

In summary,  $h$ -independence for  $\theta$  is achieved when the closest small magnitude entries in the direction of weak diffusion are included in the stencil for  $A_c$ . We avoid the  $h$ -dependent sparsity pattern of  $\tilde{A}_c$  by using  $\hat{\mathcal{N}}_c$  from (3.1) as the minimal sparsity pattern, which for this example is

$$\hat{\mathcal{N}}_c := \begin{bmatrix} & * & \\ * & * & * \\ & * & \end{bmatrix}. \quad (3.4)$$

The use of this heuristic minimal sparsity pattern is critical because the high- and low-energy heuristics (2.12b) and (2.13a) do not prevent the sparsity pattern of  $\tilde{A}_c$  from being chosen. Moreover the classical concept of strength-of-connection cannot find a suitable sparsity pattern here, and if it were employed to determine  $\hat{\mathcal{N}}_c$  based on  $A_g$ , then the pattern for  $\tilde{A}_c$  would be chosen. On the other hand, it is important that the minimal pattern  $\hat{\mathcal{N}}_c$  is restrictive enough to exclude connections in  $A_g$  that represent longer distance connections on the fine grid.

**Improving the Sparsity Pattern.** Next, we improve  $\hat{\mathcal{N}}_c$  by enforcing the heuristic (2.12b) through the following procedure, in order to target accuracy for mid-range to high energy modes. Let the set of neighbors of  $i$  in  $\mathcal{N}_c$  (i.e., the allowed nonzeros in row  $i$ ) be

$$\mathcal{N}_{ci} = \{j, \text{ such that the tuple } (i, j) \in \mathcal{N}_c\}.$$

The procedure then begins by initializing the pattern  $\mathcal{N}_c$  with the pattern of  $A_g$ . Entries are then removed from  $\mathcal{N}_c$ , starting with the smallest in magnitude, until any further removal of entries would violate

$$2 \sum_{j \notin \mathcal{N}_{ci}} |a_{ij}^g| \leq \gamma \sum_j |a_{ij}^g|. \quad (3.5)$$

**Algorithm 2:** ComputeSparsity( $A_g, P, P_I$ )

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1 Input:  $A_g$                                 {Galerkin operator}
2            $P$                                 {Interpolation operator}
3            $P_I$                               {Injection operator}
4
5  $\mathcal{N}_c \leftarrow \emptyset$ 
6 for  $(i, j)$  such that  $a_{ij}^g \neq 0$  do
7      $\mathcal{N}_c \leftarrow \mathcal{N}_c \cup \{(i, j)\}$       {Initial pattern}
8
9 for  $i = 1$  to  $nrows(A_g)$  do
10   Initialize set  $\mathcal{K}$ :  $\mathcal{K}_m$  is index of  $m$ th smallest off-diagonal nonzero in row  $i$ 
11   for  $m = 1$  to  $|\mathcal{K}|$  do
12     if  $2 \sum_{j \notin \mathcal{N}_{ci} \setminus \mathcal{K}_m} |a_{ij}^g| \leq \gamma \sum_j |a_{ij}^g|$       {Equation (2.12b) satisfied}
13     then
14        $\mathcal{N}_{ci} \leftarrow \mathcal{N}_{ci} \setminus \mathcal{K}_m$       {Remove entry  $\mathcal{K}_m$ }
15
16 for  $(i, j)$  such that  $(P_I^T A P + P^T A P_I)_{ij} \neq 0$  do
17    $\mathcal{N}_c \leftarrow \mathcal{N}_c \cup \{(i, j)\}$       {Union with minimal pattern}
18 return  $\mathcal{N}_c$ 

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Assuming classical stencil collapsing will be done to compute final matrix entry values (as outlined in Section 3.2), this procedure guarantees (2.12b) for the final  $A_c$ , even before the stencil collapsing step. The factor of 2 essentially represents the change made to  $A_g$  when dropping an entry, plus the maximum change to  $A_g$  possible when collapsing that entry to the allowed nonzero entries. Last, we ensure the minimal sparsity pattern from (3.1), by taking the union of  $\mathcal{N}_c$  and  $\hat{\mathcal{N}}_c$ , i.e., we replace  $\mathcal{N}_c$  with  $\mathcal{N}_c \cup \hat{\mathcal{N}}_c$ . Algorithm 2 gives a detailed description of this process. If a symmetric pattern is desired,  $\mathcal{N}_c$  can be symmetrized, such that if  $(i, j) \in \mathcal{N}_c$ , then  $(j, i)$  is added to the set  $\mathcal{N}_c$  as well.

**3.2. Eliminating Entries in  $A_g$  for Scalar Problems.** The goal when eliminating entries in  $A_g$  to obtain  $A_c$  is to not change the action on the near null space of  $A_g$ . We rely on the sparsity pattern choice from Section 3.1 to avoid changing the action on other modes. We eliminate entries in  $A_g$  based on a classical AMG stencil collapsing approach, because this approach has been used for decades [6, 14, 18] to develop interpolation formulas which are accurate for the constant-based near null space modes critical for classical scalar problems. In other words, this lumping procedure is (roughly speaking) as effective at preserving the near null space as classical AMG interpolation is accurate for the near null space.

The dropping strategy begins by initializing  $A_c$  as a copy of  $A_g$ . Then, each  $a_{ij}^c \neq 0$  such that  $(i, j) \notin \mathcal{N}_c$  is eliminated from  $A_c$ . The stencil collapsing algorithm eliminates  $a_{ij}^c$  by adding a fraction of that entry to each of  $j$ 's strongly connected neighbors in row  $i$ . The fractional lumping is done such that the row sum does not change and the local constant-based near null space is thus unchanged. We begin by letting  $S$  be the strength-of-connection matrix defined by the classical AMG measure with respect to  $A_g$ , and define the neighbors of  $j$  in  $S$  as

$$\mathcal{N}_{sj} = \{k, \text{ such that } s_{jk} \neq 0\}. \quad (3.6a)$$

Next, we find  $U$ , which represents the strong connections of  $j$  shared by the nonzero pattern of row  $i$ , that is

$$U = \mathcal{N}_{sj} \cap \mathcal{N}_{ci}. \quad (3.6b)$$

This set  $U$  represents the unknowns to which  $a_{ij}^c$  will be lumped. If strong neighbors are found ( $U \neq \emptyset$ ), we avoid changing the diagonal and remove  $i$  from  $U$ . This avoids changing



**Algorithm 3:** NonGalerkin( $A_g, S, \mathcal{N}_c$ )

---

```

1 Input:  $A_g$  {Galerkin operator}
2  $S$  {Strength-of-connection operator based on  $A_g$ }
3  $\mathcal{N}_c$  {Desired sparsity pattern}
4
5  $A_c \leftarrow A_g$  {Initialize with Galerkin coarse grid}
6 for  $i = 1$  to  $nrows(A_c)$  do
7   for  $j$  such that  $a_{ij} \neq 0$  do
8     if  $j \notin \mathcal{N}_{ci}$  then
9        $U \leftarrow \mathcal{N}_{sj} \cap \mathcal{N}_{ci}$ 
10      if  $U = \emptyset$  or  $U = \{i\}$  then
11         $a_{ii}^c \leftarrow a_{ii}^c + a_{ij}^c$  {No neighbors, lump to diagonal}
12      else
13         $U \leftarrow U \setminus \{i\}$  {Avoid changing diagonal}
14         $\sigma = \sum_{k \in U} |s_{jk}|$ 
15        for  $k \in U$  do
16           $a_{ik}^c \leftarrow a_{ik}^c + (|s_{jk}|/\sigma) a_{ij}^c$  {Lump to neighbors}
17         $a_{ij}^c \leftarrow 0$ 
18      else
19        Do nothing
20  $A_c \leftarrow 0.5(A_c^T + A_c)$  {Symmetrize}
21 for  $i = 1$  to  $nrows(A_c)$  do
22    $a_{ii}^c \leftarrow a_{ii}^c + \sum_j a_{ij}^g - \sum_j a_{ij}^c$  {Preserve row sum}
23 return  $A_c$ 

```

---

the center of each row's Gershgorin disc, if possible. If the diagonal entry of the matrix is changed too much, then the scale of that equation will subsequently change, and we have observed this being detrimental to performance. We then compute the fractions by which the entry will be lumped, and carry out the fractional lumping such that the near null space is preserved and  $E\mathbf{1} = 0$ :

$$\sigma = \sum_{k \in U} |s_{jk}| \quad (3.6c)$$

$$a_{ik}^c \leftarrow a_{ik}^c + (|s_{jk}|/\sigma) a_{ij}^c \quad \text{for } k \in U. \quad (3.6d)$$

Similar to classical stencil collapsing, if no strong neighbors are found ( $U = \emptyset$ ), the entry is lumped to the diagonal. After all entries are eliminated, the matrix  $A_c$  may be symmetrized,

$$A_c \leftarrow 0.5(A_c^T + A_c), \quad (3.6e)$$

followed by diagonal lumping to preserve row sum,

$$a_{ii}^c \leftarrow a_{ii}^c + \sum_j a_{ij}^g - \sum_j a_{ij}^c. \quad (3.6f)$$

Algorithm 3 describes in detail this stencil collapsing algorithm. In Section 3.3 we show how this procedure produces an identical collapsing operator to that used by classical AMG interpolation strategies.

While the stencil collapsing process preserves the row sum of the operator, the preservation of symmetry in line 20 changes this row sum. Thus, line 22 is required to modify the diagonal and preserve the row sum. The values added to the diagonal in line 22 are typically small, but necessary for maintaining accuracy for the near null space of the operator. From a

different point of view, this symmetrization step can be thought of as a way of symmetrically dropping entries, where lines 15 and 16 are replaced with

$$\text{for } k \in U \text{ do } \quad a_{ik}^c \leftarrow a_{ik}^c + (1/2)(|s_{jk}|/\sigma)a_{ij}^c \quad (3.7a)$$

$$a_{ki}^c \leftarrow a_{ki}^c + (1/2)(|s_{jk}|/\sigma)a_{ij}^c, \quad (3.7b)$$

followed by a fix up step that lumps to the diagonal to preserve row sum.

REMARK 1. *The symmetrization steps (3.7a) and (3.7b) disturb the property (2.12b), which had been guaranteed with (3.5). We have not observed in our experiments that the symmetrization step changes (3.5) significantly. So, while the property (2.12b) could be guaranteed by another processing step after symmetrization, we have not found it to be needed.*

REMARK 2. *We lump entries to the diagonal in line 11 when no strong neighbors are found ( $U = \emptyset$ ). However, these entries may also be left in the matrix. In our experiments, few entries were lumped to the diagonal, so the impact on complexity is small. This question remains a topic of active research.*

REMARK 3. *The stencil collapsing approach of Algorithms 2 and 3 does preserve definiteness for  $M$ -matrices. An  $M$ -matrix is a common multigrid operator where the diagonal is positive, all off-diagonals are non-positive, and row sums are non-negative. Thus by a Gershgorin disc argument,  $M$ -matrices are at least positive semi-definite. When the proposed approach operates on an  $M$ -matrix, all off-diagonals remain non-positive (off-diagonals are changed only by adding a negative value); the diagonal remains positive; and the row sum is unchanged. Thus the resulting  $A_c$  is still an  $M$ -matrix and hence definite. If the symmetrization step is done, then  $A_c$  is SPD. If the interpolation method chosen preserves the  $M$ -matrix property on coarse grids, then the proposed method will still yield an SPD preconditioner. However for general matrices, there is no way to guarantee that the proposed method preserves definiteness. Avoiding a loss of definiteness is a topic of active research, but we note that in our experiments accelerating GMRES and CG with the method led to similar results, implying that no significant loss of definiteness occurred for the test problems considered.*

In summary, this algorithm removes entries from a coarse grid operator in a way that preserves the spectrum for constant-like near null space modes. The algorithm relies on the choice of  $\mathcal{N}_c$  to guarantee that the resulting coarse grid is accurate for mid-range to high energy modes. Additionally, the algorithm relies primarily on local row-wise computations that require little communication, making the method well suited for the parallel setting.

**3.3. Eliminating Entries in  $A_g$  in a General Setting.** In this section, we consider the case where the matrix requires stencil collapsing that preserves multiple modes in  $B$ , i.e., we must enforce heuristic (2.13b) when  $B$  has multiple columns. The motivation is to extend the proposed method to problems such as elasticity, where the near null space consists of multiple vectors, e.g., the rigid-body modes. We first present classical stencil collapsing in terms of the general approach, and then discuss one way to extend this perspective to the multiple mode case.

Consider Figure 3.1, where the matrix graph relative only to unknown 1 is depicted, and a local ordering is used. In the picture, unknowns 5 and 6 are to be eliminated from the stencil, and collapsed to unknowns 2, 3 and 4. The gray dotted lines and associated weights represent strength-of-connection couplings between 5 and 6 relative to their neighbors 2, 3 and 4. The strength-of-connection couplings have been normalized such that the two connections for unknown 5 sum to 1, and likewise for unknown 6.

Let the set of off-diagonal unknowns that are maintained in row  $i = 1$  be denoted by

$$\mathcal{N}_{ci} = \{2, 3, 4\}, \quad (3.8)$$

and the set of off-diagonal unknowns to be eliminated be denoted by

$$\chi_i = \mathcal{N}_{gi} \setminus \mathcal{N}_{ci} = \{5, 6\}, \quad (3.9)$$

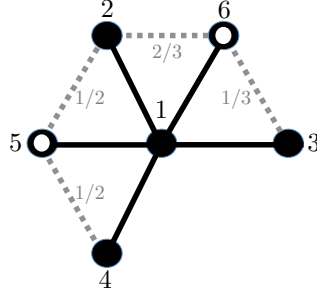


Fig. 3.1: Stencil collapsing example.

Then the corresponding generalization for classical stencil collapsing can be represented with a local interpolation-like operator  $G_i$ , that operates only on nonzero entries, i.e.,

$$[a_{ii}^c \quad (\mathbf{a}_i^c|_{\mathcal{N}_{ci}})^T] = [a_{ii}^g \quad (\mathbf{a}_i^g|_{\mathcal{N}_{ci}})^T \quad (\mathbf{a}_i^g|_{\chi_i})^T] \begin{bmatrix} 1 & 0 \\ 0 & I \\ 0 & G_i \end{bmatrix} \quad (3.10a)$$

where  $\mathbf{a}_i^c|_{\mathcal{N}_{ci}}$  is the vector of off-diagonal entries after stencil collapsing,  $a_{ii}^c = a_{ii}^g$ , and

$$G_i = \begin{bmatrix} 1/2 & 0 & 1/2 \\ 2/3 & 1/3 & 0 \end{bmatrix}. \quad (3.10b)$$

Note that all other entries in row  $i$  of  $A_c$  are zero. The entry  $(G_i)_{0k}$  represents the normalized strength-of-connection entry between unknowns 5 and  $k$ , and  $(G_i)_{1k}$  likewise corresponds to unknown 6. More precisely, recall the definition of  $U \leftarrow \mathcal{N}_{sj} \cap \mathcal{N}_{ci}$  for each row  $i$  from Algorithm 3, and define  $G_i$  as

$$G_i \in \mathbb{R}^{|\chi_i| \times |\mathcal{N}_{ci}|} \quad (3.11a)$$

$$(G_i)_{uv} = \frac{s(\chi_i)_u, (\mathcal{N}_{ci})_v}{\sum_{k \in U} |s(\chi_i)_{u,k}|} \quad (3.11b)$$

In summary, the operator  $G_i$  interpolates from unknowns in  $\mathcal{N}_{ci}$  to unknowns in  $\chi_i$  using normalized strength-of-connection values that interpolate between strongly connected unknowns, and preserve near null space mode(s). For this example, all row sums of  $G_i$  equal 1. In general, classical stencil collapsing will always result in a row sum of 1 in  $G_i$ .

REMARK 4. Equation (3.10a) defines the general case of stencil collapsing, but it does not allow for entries to be lumped to the diagonal as in the Algorithm 3. This can be observed because the first column is all zero, except for the (1,1) entry. This was an engineering choice meant to protect the diagonal entry from large changes during the process of fitting multiple modes into the span of  $G_i$ , which can cause relatively large changes to entries. For the case when an  $a_{ij}$  is being eliminated and this results in  $U = \{i\}$  or  $U = \emptyset$ , then that  $a_{ij}$  is not eliminated and remains in the matrix. Lumping this entry to the diagonal is an option and would result in a small change, but we choose to maintain a consistent approach here and leave the diagonal unchanged in all cases. This does not change the resulting algorithmic behavior because very few such  $a_{ij}$  are traversed in our test cases.

On the other hand in Algorithm 3, the changes to the diagonal are guaranteed to be small through the choice of  $\gamma$ . So, we allow these small changes in order to drop entries as aggressively as possible.

**3.3.1. Accommodating Multiple Near Null Space Modes.** We now present the generalized stencil collapsing case, where  $G_i$  is post-processed to accommodate multiple near null space modes. This set of vectors  $B$  is usually specified on the finest level, and

**Algorithm 4:** Generalized\_NonGalerkin( $A_g, S, \mathcal{N}_c, B$ )

---

```

1 Input:  $A_g$  {Galerkin operator}
2  $S$  {Strength-of-connection operator based on  $A_g$ }
3  $\mathcal{N}_c$  {Desired sparsity pattern}
4  $B$  {Near null space modes for  $A_g$ , ordered in importance}
5
6  $A_c \leftarrow A_g$  {Initialize with Galerkin coarse grid}
7 for  $i = 1$  to  $nrows(A_c)$  do
8    $k_i \leftarrow \max\left(\left\lfloor \frac{|\mathcal{N}_{ci}|}{2} \right\rfloor - 2, 1\right)$  {Use first  $k_i$  columns of  $B$ }
9   Compute  $G_i$  {Equation (3.11)}
10   $F \leftarrow B|_{\chi_i} - G_i B|_{\mathcal{N}_{ci}}$  {Compute update to  $G_i$ }
11  for  $j = 1$  to  $nrows(G_i)$  do
12    Let  $\mathbf{f}$  and  $\mathbf{g}$  be row  $j$  of  $F$  and  $G_i$ , respectively.
13     $\mathbf{u} \leftarrow \operatorname{argmin}_{\mathbf{u}} \|(B|_{\mathcal{N}_{ci}})^T \mathbf{u}^T - \mathbf{f}^T\|_2^2$ 
14     $\mathbf{g} \leftarrow \mathbf{g} + \mathbf{u}$ 
15     $\begin{bmatrix} a_{ii}^c & (\mathbf{a}_i^c|_{\mathcal{N}_{ci}})^T \end{bmatrix} = \begin{bmatrix} a_{ii}^g & (\mathbf{a}_i^g|_{\mathcal{N}_{ci}})^T & (\mathbf{a}_i^g|_{\chi_i})^T \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & I \\ 0 & G_i \end{bmatrix}$  {Equation (3.10a)}
16     $\mathbf{a}_i^c|_{\chi_i} \leftarrow 0$  {Zero out entries not in pattern}
17 return  $A_c$ 

```

---

then transferred to each coarse level with the restriction operator  $P_f^T B$ . Multigrid methods typically require a set of such modes for construction of interpolation. Even classical AMG methods implicitly assume  $B = \mathbf{1}$  by virtue of the interpolation formulas which are explicitly designed to preserve the constant.

Our strategy updates the  $G_i$  from classical stencil collapsing in a least-squares fashion so that  $G_i$  interpolates multiple vectors  $B$  accurately. The intention is that the minimal update results in a  $G_i$  with weights that still favor strong connections. More precisely, we update  $G_i$  in a minimal 2-norm sense to fit  $B$  and satisfy

$$G_i B|_{\mathcal{N}_{ci}} = B|_{\chi_i}, \quad (3.12a)$$

where

$$B|_{\mathcal{N}_{ci}} = B_{uv} \quad \text{for } u \in \mathcal{N}_{ci} \text{ and } v \in \{0, 1, 2, \dots, ncols(B)\} \quad (3.12b)$$

$$B|_{\chi_i} = B_{uv} \quad \text{for } u \in \chi \text{ and } v \in \{0, 1, 2, \dots, ncols(B)\}. \quad (3.12c)$$

This property guaranties that the action of  $A_c B = A_g B$ . To see how (3.12a) accomplishes this, take equation (3.10a) and right multiply by

$$\begin{bmatrix} \mathbf{b}_i^T \\ B|_{\mathcal{N}_{ci}} \end{bmatrix}, \quad (3.13)$$

using the identity (3.12a). The quantity  $\mathbf{b}_i^T$  represents  $B$  restricted to the  $i$ th row. We now describe in Algorithm 4 the generalized approach to stencil collapsing. For the experiments considered here, the sparsity pattern argument  $\mathcal{N}_c$  is generated by Algorithm 2.

In addition to Remark 4, there are some important algorithmic notes to make. When solving PDE systems, such as elasticity, where an unknown  $j$  belongs to only one of many PDEs, it is critical to limit the collapsing to occur between unknowns in the same PDE. This can easily be implemented in Algorithm 4 by pre-filtering the strength matrix  $S$  with

$$s_{ij} \leftarrow 0 \quad \text{if } \text{PDE\_num}(i) \neq \text{PDE\_num}(j), \quad (3.14)$$

where the function `PDE_num()` returns the PDE number (say 0, 1 or 2) for an unknown. In order to compute the PDE number for a coarse unknown, we utilize the *C/F* splitting present at each level to find the corresponding fine grid unknown for each coarse grid unknown. Another algorithm note concerns the computation of line 13 where  $(B|\mathcal{N}_{ci})^T$  may be ill-conditioned. This system is currently solved through an SVD approach and determining appropriate singular value cut-offs is a topic of future work.

REMARK 5. *We have observed issues with over fitting and the computation of  $G_i$ . As an example, let  $G_i$  have 4 nonzeros per row, and  $B$  contain 4 or 5 vectors, then the process of computing  $G_i$  to exactly preserve all modes is ill conditioned, i.e., small changes to  $B$  can result in large changes to  $G_i$ . We have observed this phenomenon for the model 2D rotated anisotropic diffusion problems in the results section, when  $B$  equals the constant, linears and quadratics. Here, the coefficients computed for  $G_i$  would sometimes vary by 2 or 3 orders of magnitude. The resulting coarse grid stencil became inaccurate, and the overall AMG cycle deteriorated or diverged as a result. As a solution, we take only the first  $k_i$  columns of  $B$  when computing  $G_i$ . It is assumed that  $B$  is ordered in importance, so that the first  $k_i$  vectors are the most critical ones. For this experiment, the vectors were ordered constant, linears and quadratics, so that when vectors were discarded from  $B$ , they represented a quadratic function. We choose  $k_i$  to be significantly smaller than the number of nonzeros per row in  $G_i$ , or  $k = |\mathcal{N}_{ci}|/2$ , where  $|\mathcal{N}_{ci}|$  is the number of unknowns in  $\mathcal{N}_{ci}$ . Thus, the number of modes in  $B$  used to compute  $G_i$  can change with  $i$ . While this strategy is purely an engineering choice, it is a reasonable number of modes to choose from  $B$  to avoid over fitting.*

**4. Evaluating the Accuracy of the Stencil Collapsing Approach.** In this section, we describe a near optimal non-Galerkin coarse grid operator, and compare it to our method for model diffusion problems. Let  $(\mathbf{a}_i^c)^T$  be the  $i$ th row of  $A_c$  and let  $\lambda_j$  and  $\mathbf{v}_j$  be the eigenvalues and eigenvectors of  $A_g$ . Below, we derive an upper bound for  $\theta$  in (2.2) in terms of  $\mathbf{a}_i^c$ ,  $\lambda_j$  and  $\mathbf{v}_j$ . In (4.1d), we write  $\mathbf{x} = \sum_j \alpha_j \mathbf{v}_j$ , with  $\alpha_j \in [0, 1]$  and  $\sum_j |\alpha_j| = 1$ . In (4.1e), we can reverse the order of the min-max problem because it is quadratic in  $\alpha_j$  and  $a_{ij}^c$ . A useful upper bound on the minimal  $\theta$  is then

$$\theta_{\min}^2 = \min_{A_c \in \mathcal{N}_c} \|(I - A_c A_g^{-1})\|_2^2 \quad (4.1a)$$

$$= \min_{A_c \in \mathcal{N}_c} \max_{\|\mathbf{x}\|_2=1} \|(I - A_c A_g^{-1})\mathbf{x}\|_2^2 \quad (4.1b)$$

$$= \min_{A_c \in \mathcal{N}_c} \max_{\|\mathbf{x}\|_2=1} \sum_i ((\mathbf{x})_i - (\mathbf{a}_i^c)^T A_g^{-1} \mathbf{x})^2 \quad (4.1c)$$

$$= \min_{A_c \in \mathcal{N}_c} \max_{\|\boldsymbol{\alpha}\|_2=1} \sum_i \left( \sum_j \alpha_j (v_{ij} - \lambda_j^{-1} \mathbf{v}_j^T \mathbf{a}_i^c) \right)^2 \quad (4.1d)$$

$$= \max_{\|\boldsymbol{\alpha}\|_2=1} \min_{A_c \in \mathcal{N}_c} \sum_i \left( \sum_j \alpha_j (v_{ij} - \lambda_j^{-1} \mathbf{v}_j^T \mathbf{a}_i^c) \right)^2 \quad (4.1e)$$

$$= \max_{\|\boldsymbol{\alpha}\|_2=1} \sum_i \min_{\mathbf{a}_i^c \in \mathcal{N}_{ci}} \left( \sum_j \alpha_j (v_{ij} - \lambda_j^{-1} \mathbf{v}_j^T \mathbf{a}_i^c) \right)^2 \quad (4.1f)$$

$$\leq \sum_i \min_{\mathbf{a}_i^c \in \mathcal{N}_{ci}} \sum_j (v_{ij} - \lambda_j^{-1} \mathbf{v}_j^T \mathbf{a}_i^c)^2. \quad (4.1g)$$

To compute our near optimal  $A_c$ , we note that the  $\mathbf{a}_i^c$  which satisfy equation (4.1g) and

thus ultimately bound  $\theta_{\min}$  are equivalent to

$$\operatorname{argmin}_{\mathbf{a}_i^c \in \mathcal{N}_{ci}} \left\| \begin{bmatrix} \mathbf{v}_{i1} \\ \mathbf{v}_{i2} \\ \vdots \\ \mathbf{v}_{in} \end{bmatrix} - \begin{bmatrix} (1/\lambda_1)(\mathbf{v}_1^T)|_{\mathcal{N}_{ci}} \\ (1/\lambda_2)(\mathbf{v}_2^T)|_{\mathcal{N}_{ci}} \\ \vdots \\ (1/\lambda_n)(\mathbf{v}_n^T)|_{\mathcal{N}_{ci}} \end{bmatrix} (\mathbf{a}_i^c)|_{\mathcal{N}_{ci}} \right\|_2. \quad (4.2)$$

Hence, the near optimal  $A_c$  is simply constructed by solving (4.2) for each row  $i$ .

To use this tool, we compared our method to the near optimal  $A_c$  on a variety of model 2D diffusion problems which yielded small enough matrices that the computation of the near optimal  $A_c$  was possible. We asked two questions. One, is the two-level AMG convergence rate significantly better with the near optimal method when compared to the proposed approach? Two, what sparsity pattern is necessary to achieve equivalent performance to the Galerkin approach when using the near optimal method?

As an example, consider the Q1 bilinear finite element discretization on a regular structured grid with Dirichlet boundaries of the rotated anisotropic diffusion equation

$$-(c^2 + \epsilon s^2)u_{xx} - 2(1 - \epsilon)cs u_{xy} - (\epsilon c^2 + s^2)u_{yy} = f, \quad (4.3)$$

where  $\epsilon = 0.001$ ,  $c = \cos(\varphi)$ ,  $s = \sin(\varphi)$  and  $\varphi$  is the angle of rotation. We choose the angle  $\varphi = \pi/4$  (which is a particularly difficult angle for the stencil collapsing approach, on a  $15 \times 15$  grid). The stencil at the center point on the first coarse grid is given in Figures 4.1a, 4.1b, 4.1c and 4.1d for the cases of the Galerkin approach, and for the proposed stencil collapsing approach with  $\gamma = 0.03$ ,  $\gamma = 0.1$  and  $\gamma = 1.0$ . The asymptotic convergence rates for Figures 4.1a, 4.1b, 4.1c and 4.1d are 0.23, 0.23, 0.40 and 0.47, respectively. The corresponding convergence rates and stencils for the near optimal approach are nearly identical and are hence omitted. The one exception was for  $\gamma = 1.0$ , where the near optimal approach did yield a better convergence rate and slightly different coefficient values in the cross-stream direction. Thus, the conclusion is two-fold. One, that the longer distance connections present in Figure 4.1b, but not present in Figures 4.1c and 4.1d, are necessary to regain the performance of the Galerkin approach when using either the near optimal or stencil collapsing approach. Two, the coefficients computed by stencil collapsing yield similar performance to that achieved by fitting the eigenvectors in the near optimal approach.

A number of different angles and finite difference approximations for isotropic and anisotropic examples were explored with similar results. So, this tool led us to conclude that in general a broader sparsity pattern than  $P_I^T AP$  was needed and that  $\gamma = 0.03$  yielded such a sparsity pattern for the diffusion problems examined. This tool also allowed us to conclude that the coefficients computed by stencil collapsing are as good as the near optimal approach for smaller values of  $\gamma$ .

**5. Results.** In this section, we examine the numerical performance of the method for a variety of diffusion test problems and two 3D elasticity problems. In general, the tests use a V-cycle of RS-AMG to accelerate GMRES with a relative residual tolerance of  $10^{-8}$ . The tests also maintain identical solver parameters and only toggle the non-Galerkin method on and off, so that the standard Galerkin approach and the new method can be fairly compared. The serial tests were done using the PyAMG [4] package, while the parallel tests were done using the *hypr* [10] package, version 2.8.

**5.1. Scalar Diffusion Results.** In this section, we examine the proposed non-Galerkin method for scalar diffusion problems. V(2,2) cycles of classical RS-AMG using weighted-Jacobi are used to accelerate GMRES with a relative residual tolerance of  $10^{-8}$ . We choose a V(2,2) cycle with weighted-Jacobi so that our relaxation scheme compares well with the V(1,1) hybrid Gauss-Seidel cycle used in parallel in Section 5.3. In particular, weighted-Jacobi parallelizes well and we choose a V(2,2) cycle because a V(1,1) cycle would exhibit significantly slower AMG convergence than a V(1,1) hybrid Gauss-Seidel cycle for the test problems considered here. The Jacobi weight is  $1/\rho(D^{-1}A)$ , where  $D$  is the diagonal of  $A$ .

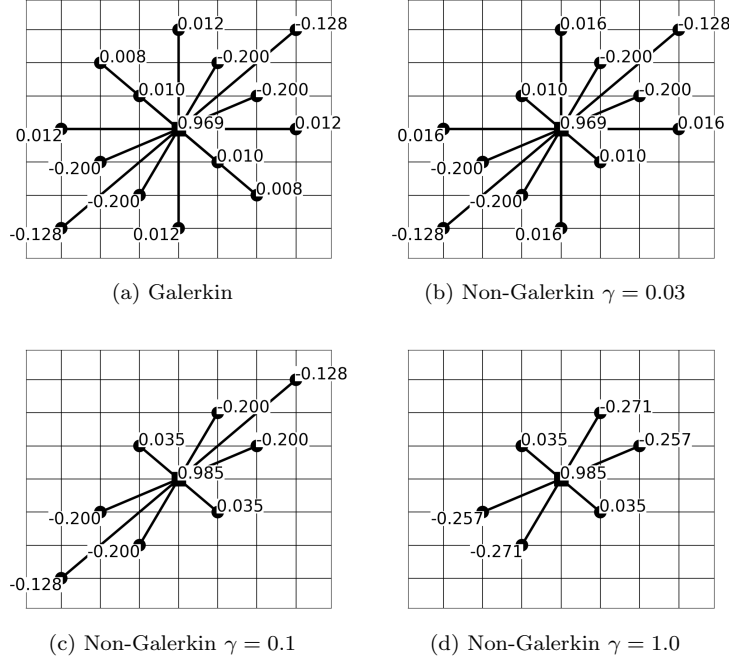


Fig. 4.1: Center point stencils for first coarse grid operators, comparing Galerkin and stencil collapsing based non-Galerkin for various  $\gamma$ .

GMRES is restarted every 15 iterations. The other RS-AMG parameters are direct interpolation, a strength-of-connection tolerance of 0.35, and first and second pass Ruge-Stüben  $C/F$  coarsening [14]. For the non-Galerkin algorithm, no post-processing symmetrization of the coarse grid operator is used, because it did not qualitatively change convergence. For all of the test problems in this subsection, including the 3D problems, 4 consecutive refinements of the initial mesh are considered in order to yield increasing matrix sizes of roughly 16 000, 64 000, 256 000 and 1 000 000.

The tables of results contain the following columns. “Max Stencil” reports the maximum stencil size over all levels, and is used as a proxy for the amount of communication induced by the AMG hierarchy. The term  $\rho_{AMG} = (\|\mathbf{r}_k\|_2 / \|\mathbf{r}_0\|_2)^{1/k}$  refers to the average convergence rate, where  $\mathbf{r}_k$  is the final residual value upon convergence after  $k$  iterations. “Op. Comp.” refers to operator complexity, which is the total number of nonzeros stored in the hierarchy, divided by the number of finest level nonzeros. “Work” refers to work per digit of accuracy, i.e., the amount of work, in fine grid matrix-vector multiplications, required to reduce the residual by one order of magnitude. This quantity is computed with  $c/|\log_{10}(\rho_{AMG})|$ , where  $c$  is the cycle complexity. The cycle complexity is the cost in floating-point operations (relative to one fine grid matrix-vector multiply) to apply one V-cycle. For a V(2,2) cycle,  $c$  equals 4 times the operator complexity because 4 relaxations are done at each level (2 going down and 2 going up). Work is particularly useful when comparing methods with differing operator complexities because similar iteration counts can represent vastly different amounts of work. A variety of  $\gamma$  values are experimented with, including the case of  $\gamma = 1.0$ , which is equivalent to using  $\hat{\mathcal{N}}_c$  as the sparsity pattern, and  $\gamma = 0.0$ , which is equivalent to using the Galerkin coarse grid approach. The overall goal of the tests is to reduce stencil size and hence parallel communication while only negligibly affecting AMG convergence.

In 2D, we consider the rotated anisotropic diffusion equation (4.3). The discretizations considered are standard second-order finite differencing and Q1 bilinear finite elements on regular structured grids with Dirichlet boundaries. Experiments are run for a variety of  $\varphi$  values, with worst case angles occurring for roughly  $\varphi \approx 2\pi/16$ , which is the test case we

choose to show in Table 5.1. While this is a worst case, it is still representative of other angles, in that as  $\gamma$  decreases to  $[0.01, 0.03]$ , the proposed approach attains similar convergence and nearly identical work units to the Galerkin approach ( $\gamma = 0.0$ ). Overall, the non-Galerkin approach is robust for these problems, and provides a reduction in operator complexity and stencil size.

$\gamma$	refinement	$\rho_{AMG}$	Op. Comp.	Work	Max stencil
1.0	0	0.28	2.3	17	16
	1	0.44	2.3	25	16
	2	0.51	2.3	32	16
	3	0.56	2.3	36	17
0.03	0	0.31	2.3	17	16
	1	0.39	2.3	23	16
	2	0.46	2.3	28	16
	3	0.50	2.3	31	16
0.01	0	0.28	2.5	19	21
	1	0.31	2.6	21	22
	2	0.35	2.6	23	21
	3	0.37	2.6	24	22
0.0	0	0.26	2.7	19	33
	1	0.28	2.7	20	33
	2	0.30	2.8	21	33
	3	0.32	2.8	23	33

Table 5.1: 2D non-Galerkin results for various  $\gamma$ , rotated anisotropic diffusion by angle of  $\varphi = 2\pi/16$ , AMG preconditioning GMRES.

The next 2D experiments concern classic coefficient jump problems. We experimented with example problems from [1] and give the results for problem IV from [1]. Here, the diffusion equation is given by

$$-\nabla \cdot (d \nabla u) = f, \quad (5.1)$$

where  $d$  is the jumpy coefficient function and the domain is depicted in Figure 5.1 with Dirichlet boundary conditions. The function  $d$  is 1000 in the shaded sawtooth region and 1 elsewhere. The grid is regular, with the coefficient jumps occurring on grid lines. However, the jumps will not be grid-aligned on the coarser grids. The discretization is the classic 5-point finite differencing scheme from [1] for coefficient jump problems. The results are similar to the other 2D experiments, in that as  $\gamma$  decreases to  $[0.01, 0.03]$ , the proposed approach exhibits similar behavior to the Galerkin approach. Overall, the non-Galerkin approach is robust for these problems, but does not provide much reduction in operator complexity and stencil size. However, this is not surprising, because the original Galerkin approach already exhibited modest complexities and stencil size growth. The main purpose of this experiment is to show the robustness of the method.

The next set of experiments examine 3D diffusion operators. We examine the problem

$$u_{xx} + \epsilon_y u_{yy} + \epsilon_z u_{zz} = f \quad (5.2)$$

using classic second-order 7-point finite differencing approximations on regular grids and also linear tetrahedral discretizations on unstructured isotropic meshes. The PDE coefficients considered are  $\epsilon_y = 1.0$ ,  $\epsilon_z = 0.001$  and  $\epsilon_y = 1.0$ ,  $\epsilon_z = 1.0$ .

The results are broadly similar, so we give a representative set in Table 5.3 for the linear tetrahedral example and isotropic coefficients ( $\epsilon_y = 1.0$ ,  $\epsilon_z = 1.0$ ). The non-Galerkin



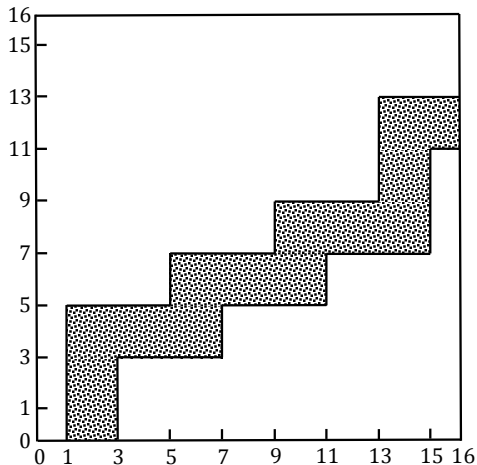


Fig. 5.1: Sawtooth coefficient jump domain.

$\gamma$	refinement	$\rho_{AMG}$	Op. Comp.	Work	Max stencil
1.0	0	0.25	2.16	14	11
	1	0.30	2.18	17	16
	2	0.51	2.19	30	14
	3	0.67	2.19	50	15
0.03	0	0.14	2.18	10	12
	1	0.15	2.19	11	14
	2	0.20	2.20	12	15
	3	0.25	2.20	15	20
0.01	0	0.14	2.19	10	13
	1	0.16	2.19	11	15
	2	0.20	2.20	12	17
	3	0.26	2.20	15	20
0.0	0	0.15	2.20	11	16
	1	0.17	2.20	11	17
	2	0.20	2.21	13	23
	3	0.28	2.21	16	23

Table 5.2: 2D non-Galerkin results for various  $\gamma$ , sawtooth coefficient jump problem, AMG preconditioning GMRES.

approach is robust, preserves the Galerkin AMG convergence rate and yields a stencil size reduction of 50%. One important note is that the operator complexity reduction is not always as dramatic as depicted in Table 5.3. For instance for the 7-point finite-differencing Poisson operator, the operator complexity reduction is only from 2.9 to 2.8, but the non-Galerkin approach still enjoys a roughly 50% stencil size reduction.

**5.2. Elasticity Results.** We next examine the proposed approach for isotropic linearized elasticity problems, where  $B \in \mathbb{R}^{n,6}$  and is equal to the six rigid body modes. Linearized elasticity is defined by

$$-\operatorname{div}(\lambda \operatorname{tr}((\nabla \mathbf{u} + \nabla \mathbf{u}^T)/2) I + \mu (\nabla \mathbf{u} + \nabla \mathbf{u}^T)) = f, \quad (5.3)$$

$\gamma$	refinement	$\rho_{AMG}$	Op. Comp.	Work	Max stencil
1.0	0	0.18	1.4	8	45
	1	0.26	1.5	10	72
	2	0.32	1.7	14	77
	3	0.40	1.8	18	78
0.03	0	0.18	1.5	8	52
	1	0.24	1.6	10	76
	2	0.30	1.8	14	81
	3	0.36	1.9	17	81
0.0	0	0.18	1.6	8	73
	1	0.24	1.8	11	91
	2	0.30	2.2	17	150
	3	0.38	2.6	24	174

Table 5.3: 3D non-Galerkin results for two  $\gamma$  choices, isotropic diffusion, AMG preconditioning GMRES.

where  $\lambda$  and  $\mu$  are the Lamé parameters,  $I$  is the identity matrix and  $\text{tr}()$  is the trace function. The GetFem++ package [13] is used to discretize. The test problem examined is a steel tripod corresponding to the mesh in Figure 5.2. Here, the tripod is discretized using linear tetrahedral elements and a downward external force is applied to the top of the tripod.

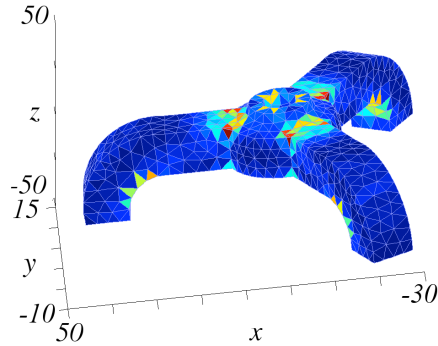


Fig. 5.2: Example tetrahedral tripod mesh.

We experiment with a different AMG solver than in Section 5.1, because the interpolation operators for RS-AMG only capture the constant vector. Hence, the experiments with RS-AMG show no performance difference when comparing Algorithm 3 with Algorithm 4 and  $B$  equal the six rigid-body modes. Essentially, if  $P^T A P$  does not accurately represent the rigid-body modes (as in the case of RS-AMG), then the stencil collapsing approach does not need to account for them. So, we consider instead a smoothed aggregation (SA) approach [12] that allows  $\text{span}(P)$  to capture all six of the rigid-body modes. Hence,  $P^T A P$  accurately represents all six of the rigid-body modes, thus making it important for the stencil collapsing approach to account for all six modes. We also choose a SA approach to show the generality of the proposed non-Galerkin method.

While SA generally does not associate  $C$ -points with the coarse grid, this set of unknowns is readily available from many standard aggregation algorithms [19] where the aggregate seed points can be used to form the set of  $C$ -points. This is done explicitly in [12] where the set of  $C$ -points is used to form  $P_I$ . The other parameters for the SA method [12] are as follows.  $V(2,2)$  cycles of weighted-Jacobi are again used to accelerate GMRES with a relative

stopping criteria of  $10^{-8}$  and a restart value of 15. The Jacobi weight is  $1/\rho(D^{-1}A)$ , where  $D$  is the diagonal of  $A$ . For consistency, the strength of connection method is the classical Ruge-Stüben method with a tolerance of 0.35. Standard greedy aggregation [19] is used.

The convergence results for the tripod example are given in Table 5.4. Three consecutive refinements are considered for increasing matrix sizes of roughly 3 000, 17 000 and 109 000. The second column denotes the values for  $B$  chosen, with “RBM” standing for the six rigid-body modes, and  $B = \mathbf{1}$  representing the standard stencil collapsing of Algorithm 3. The choice of  $B = \mathbf{1}$  is similar to collapsing with the three displacement rigid-body modes, which likely explains why Algorithm 3 performs well.

The proposed approach matches the convergence rate of the Galerkin approach for  $\gamma = 0.03$ , with a significant drop in maximum stencil size. For smaller values of  $\gamma$ , such as  $\gamma = 0.03$ , the results are nearly identical for  $B$  equalling the six rigid-body modes or the constant. This is not surprising because classical multigrid schemes based on  $B = \mathbf{1}$  are known to be effective for some simpler elasticity problems, such as this example. The use of the six rigid-body modes becomes important when the non-Galerkin algorithm is stressed with the very restricted sparsity pattern of  $\gamma = 1.0$ . Here, collapsing with respect to the rigid body modes, but not  $B = \mathbf{1}$ , allows for regaining the original work per digit of accuracy numbers of the Galerkin approach.

$\gamma$	$B$	refinement	$\rho_{AMG}$	Op. Comp.	Work	Max stencil
1.0	$\mathbf{1}$	0	0.45	1.2	12	42
		1	0.50	1.2	16	72
		2	0.64	1.2	24	97
1.0	RBM	0	0.44	1.2	12	42
		1	0.48	1.2	14	72
		2	0.54	1.2	18	97
0.03	$\mathbf{1}$ or RBM	0	0.40	1.3	11	56
		1	0.44	1.4	15	138
		2	0.48	1.5	18	245
0.0	$\mathbf{1}$ or RBM	0	0.39	1.4	11	69
		1	0.43	1.5	16	182
		2	0.47	1.6	20	346

Table 5.4: Elasticity non-Galerkin results for various  $\gamma$  and collapsing strategies, AMG preconditioning GMRES.

**5.3. Parallel Results.** In this section, we present parallel results for the simple scalar 7-point 3D isotropic diffusion finite difference operator with Dirichlet boundary conditions. The goal is to demonstrate the potential of the algorithm to speedup parallel AMG solve phase times. We therefore choose the simple 7-point model problem that nonetheless yields an unscalable growth in stencil size. The parallel stencil collapsing is identical to the serial algorithm, with a few exceptions. The collapsing is done with a binary strength-of-connection matrix (i.e., each strong connection has a value of 1.0 and each weak connection has a value of 0.0). This is done because binary strength-of-connection matrices are what is currently available in *hypre*. Implementing the complete stencil collapsing approach from Algorithm 3 using standard strength matrices is future work.

The parallel studies carried out are weak scaling tests with 25,000 unknowns per core on two different machines, one with a fast InfiniBand QDR interconnect and 6144 cores and the other with a slow InfiniBand DDR interconnect and 4096 cores. Thus, the largest problem sizes considered are 153.6 and 102.4 million unknowns, respectively. V(1,1) cycles using hybrid Gauss-Seidel [3] are used to precondition GMRES to within a relative residual

tolerance of  $10^{-8}$  using a restart parameter of 10. We note that the non-Galerkin algorithm has also been run in symmetrized mode with CG and the results have not qualitatively differed from the below results.

Two different AMG scenarios are explored in parallel, one that uses a “best practices” set of parameters, which the *hypre* developers commonly recommend, and the other that uses classical parallel AMG parameters. The *hypre* parameters for best practices are hybrid symmetric Gauss-Seidel (relax type 6), HMIS [16] coarsening (coarsen type 10), extended classical modified interpolation [15] (interpolation type 6), aggressive coarsening [16] on the finest level (aggressive num levels 1), truncated interpolation to 5 entries per row (`PMaxElmts` option equals 5) and a strength of connection tolerance of 0.25. The *hypre* parameters for classical parallel AMG are hybrid symmetric Gauss-Seidel (relax type 6), classical modified interpolation (interpolation type 0), Falgout coarsening [9] (coarsen type 0), and a strength of connection tolerance of 0.55. We note that it is typical to use a higher strength tolerance in this case. We examine the non-Galerkin approach for  $\gamma = 0.03$ , which is a representative  $\gamma$  value that worked well over all the serial test problems, and for  $\gamma = 0.0$ , which corresponds to standard Galerkin AMG

We first report in Tables 5.5 and 5.6 the convergence, operator complexity, work and maximum stencil size over all levels for the best practices parameters and classical parallel AMG parameters, respectively. We do this for the four largest core counts (problem size equals 25K times the core count). The results are similar to the serial case, in that the non-Galerkin approach attains a similar AMG convergence rate, but results in a significantly smaller maximum stencil size. For the case of classical parallel AMG, which has always been plagued by high complexities, there is also a significant reduction in operator complexity that makes this method more practical. In addition, the convergence rate for non-Galerkin is noticeably better for classical parallel AMG, although the reasons for this are difficult to discern in the multilevel setting. In the two-level setting, the convergence rates do not significantly differ.

$\gamma$	ncores	$\rho_{AMG}$	Op. Comp.	Work	Max stencil
0.03	768	0.33	1.25	10	82
	1536	0.33	1.26	10	81
	3072	0.36	1.26	11	85
	6144	0.37	1.25	11	96
0.0	768	0.33	1.37	11	184
	1536	0.36	1.37	12	188
	3072	0.40	1.37	14	191
	6144	0.39	1.37	13	206

Table 5.5: “Best practices” AMG results for two  $\gamma$  choices, isotropic diffusion, AMG preconditioning GMRES.

Next, we report speedup and time to solution for the AMG solve phase in order to verify that the observed reduction in stencil size results in a faster runtime. Since this is a feasibility study and in order to simplify the parallel implementation, the non-Galerkin part of the AMG setup phase has not been written with attention to performance. So, we do not report setup phase timings, as they would not be informative. We do note that even with the unoptimized code, we always see a reduction in setup phase time for classical parallel AMG, and for best practices AMG, some machines also already show a reduction in setup phase time. A full timing comparison is ongoing work and will require optimizing the setup phase and parameters such as different  $\gamma$  choices on coarse levels.

Figures 5.3a and 5.3b show the speedup and timings for the best practices scenario and classical parallel AMG scenario, respectively, on the machine with a fast interconnect. The

$\gamma$	ncores	$\rho_{AMG}$	Op. Comp.	Work	Max stencil
0.03	768	0.19	4.8	27	381
	1536	0.20	5.0	29	380
	3072	0.20	5.2	30	435
	6144	0.21	5.5	32	463
0.0	768	0.22	8.4	51	1266
	1536	0.24	9.0	58	1286
	3072	0.27	9.4	66	1405
	6144	0.29	9.7	72	1479

Table 5.6: “Classical parallel AMG” results for two  $\gamma$  choices, isotropic diffusion, AMG preconditioning GMRES.

speedup is on the left axis for the dotted line, and the time to solution for the AMG solve phase is on the right axis for the two solid lines depicting the Galerkin and non-Galerkin approaches. For the best practices scenario, there is a speedup of 15–20%, but for the classical parallel AMG scenario, the speedup grows to 250%. Figures 5.4a and 5.4b depict the similar results for the machine with a slow interconnect, but with more pronounced speedups of 150% and 400% for the best practices and classical parallel AMG scenarios, respectively.

These results are encouraging, in part because the speedup grows with number of cores. Thus, we expect this approach to yield even better speedups when moving to current Petascale machines ( $10^6$  cores) and also to next generation exascale machines ( $10^6$ – $10^9$  cores).

Moreover, the results raise the question whether the current best practices in AMG can be avoided altogether, in favor of a more classical AMG approach that leverages non-Galerkin coarse grids. For instance, if the overall time is compared between the best practices and classical parallel AMG scenarios for each machine, it is observed that the non-Galerkin approach for the classical scenario is competitive with the Galerkin approach for the best practices scenario. This rethinking of parallel AMG is attractive because the current best practices for reducing stencil size and communication (i.e., aggressive coarsening and extended interpolation) also worsen the AMG convergence rate, whereas non-Galerkin coarse grids target the same reduced stencil size and associated reduced communication, but with no deterioration in the AMG convergence rate. For example, our parallel tests for a 27-point finite element discretization of the Poisson problem already show the fastest AMG solve phase time is for classical parallel AMG coupled with the non-Galerkin approach. Regardless of which AMG scenario used, the non-Galerkin approach provides a parallel performance benefit.

**6. Comments/Conclusions.** In conclusion, the proposed non-Galerkin approach is an effective method at reducing coarse grid stencil size and parallel communication, while having a negligible effect on the AMG convergence rate for the problems considered here. In particular, the method relies primarily on row-wise computations in parallel, thus making it a relatively inexpensive method with respect to communication. Additionally, as indicated by our experiments, the proposed method is applicable to most AMG codes, include classical RS-AMG and SA.

There are some outstanding issues, including the importance of maintaining symmetry and definiteness on coarse grids. While theoretically attractive, we have not observed maintenance of symmetry being critical to performance, even out to 150 million unknowns in parallel. However, we will maintain this option in our code as we continue experiments on more real world test problems. Maintaining definiteness on coarse grids, outside of the case of M-matrices, will continue to be a future research issue.

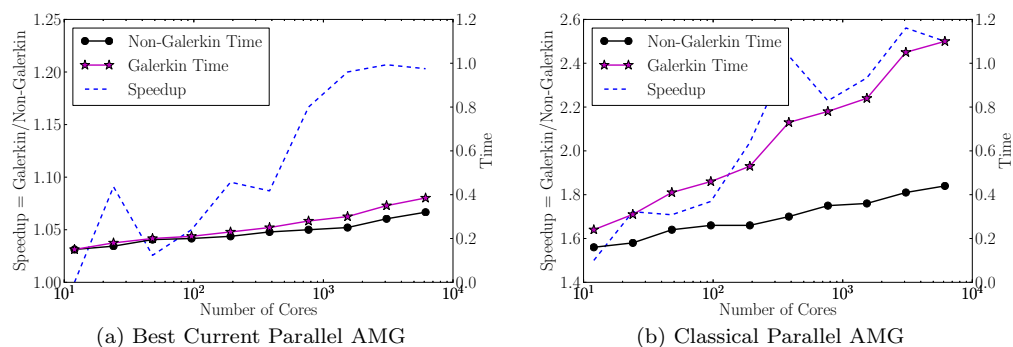


Fig. 5.3: Speedup and AMG solve phase timings comparing non-Galerkin AMG and Galerkin AMG on machine with *fast* network.

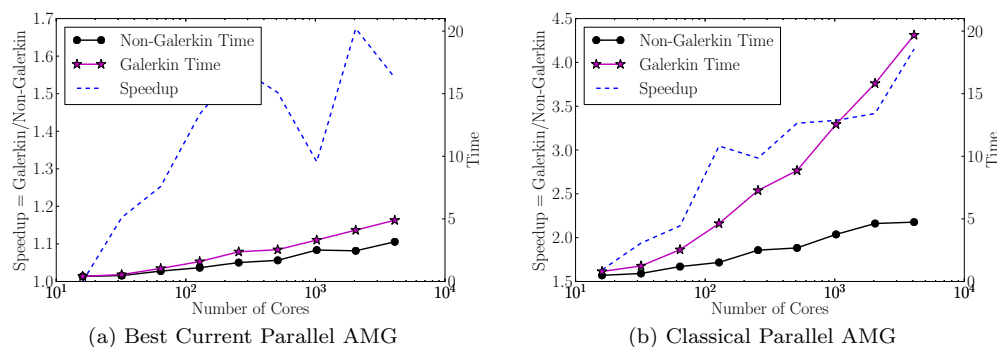


Fig. 5.4: Speedup and AMG solve phase timings comparing non-Galerkin AMG and Galerkin AMG on machine with *slow* network.

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