

Nonsymmetric Multigrid Preconditioning for Conjugate Gradient Methods

Bouwmeester, H.; Dougherty, A.; Knyazev, A.V.

TR2013-027 June 2013

Abstract

We numerically analyze the possibility of turning off post-smoothing (relaxation) in geometric multigrid when used as a preconditioner in conjugate gradient linear and eigenvalue solvers for the 3D Laplacian. The geometric Semicoarsening Multigrid (SMG) method is provided by the hypre parallel software package. We solve linear systems using two variants (standard and exible) of the preconditioned conjugate gradient (PCG) and preconditioned steepest descent (PSD) methods. The eigenvalue problems are solved using the locally optimal block preconditioned conjugate gradient (LOBPCG) method available in hypre through BLOPEX software. We observe that turning off the post-smoothing in SMG dramatically slows down the standard PCG-SMG. For exible PCG and LOBPCG, our numerical results show that post-smoothing can be avoided, resulting in overall acceleration, due to the high costs of smoothing and elatively insignificant decrease in convergence speed. We numerically demonstrate for linear systems that PSD-SMG and exible PCG-SMG converge similarly if SMG post-smoothing is off. We experimentally show that the effect of acceleration is independent of memory interconnection. A theoretical justification is provided.

Cornell University Library

This work may not be copied or reproduced in whole or in part for any commercial purpose. Permission to copy in whole or in part without payment of fee is granted for nonprofit educational and research purposes provided that all such whole or partial copies include the following: a notice that such copying is by permission of Mitsubishi Electric Research Laboratories, Inc.; an acknowledgment of the authors and individual contributions to the work; and all applicable portions of the copyright notice. Copying, reproduction, or republishing for any other purpose shall require a license with payment of fee to Mitsubishi Electric Research Laboratories, Inc. All rights reserved.

Nonsymmetric multigrid preconditioning for conjugate gradient methods

Henricus Bouwmeester
University of Colorado Denver
P.O. Box 173364
Campus Box 170
Denver, CO 80217-3364
Henricus.Bouwmeester@ucdenver.edu

Andrew Dougherty
University of Colorado Denver
P.O. Box 173364
Campus Box 170
Denver, CO 80217-3364
Andrew.Dougherty@ucdenver.edu

Andrew V. Knyazev
Mitsubishi Electric Research
Laboratories
201 Broadway
Cambridge, MA 02145
Andrew.Knyazev@merl.com

ABSTRACT

We numerically analyze the possibility of turning off post-smoothing (relaxation) in geometric multigrid when used as a preconditioner in conjugate gradient linear and eigenvalue solvers for the 3D Laplacian. The geometric Semicoarsening Multigrid (SMG) method is provided by the *hypr* parallel software package. We solve linear systems using two variants (standard and flexible) of the preconditioned conjugate gradient (PCG) and preconditioned steepest descent (PSD) methods. The eigenvalue problems are solved using the locally optimal block preconditioned conjugate gradient (LOBPCG) method available in *hypr* through BLOPEX software. We observe that turning off the post-smoothing in SMG dramatically slows down the standard PCG-SMG. For flexible PCG and LOBPCG, our numerical results show that post-smoothing can be avoided, resulting in overall acceleration, due to the high costs of smoothing and relatively insignificant decrease in convergence speed. We numerically demonstrate for linear systems that PSD-SMG and flexible PCG-SMG converge similarly if SMG post-smoothing is off. We experimentally show that the effect of acceleration is independent of memory interconnection. A theoretical justification is provided.

Keywords: linear equations; eigenvalue; iterative; multigrid; smoothing; pre-smoothing; post-smoothing; preconditioning; conjugate gradient; steepest descent; convergence; parallel software; *hypr*; BLOPEX; LOBPCG.

1. INTRODUCTION

Smoothing (relaxation) and coarse-grid correction are the two cornerstones of multigrid technique. In algebraic multigrid, where only the system matrix is (possibly implicitly) available, smoothing is more fundamental since it is often used to construct the coarse grid problem. In geometric multigrid, the coarse grid is generated by taking into account the geometry of the fine grid, in addition to the chosen smoothing procedure. If full multigrid is used as a stand-

alone solver, proper smoothing is absolutely necessary for convergence. If multigrid is used as a preconditioner in an iterative method, one is tempted to check what happens if smoothing is turned partially off.

For symmetric positive definite (SPD) linear systems, the preconditioner is typically required to be also a fixed linear SPD operator, to preserve the symmetry of the preconditioned system. In the multigrid context, the preconditioner symmetry is achieved by using balanced pre- and post-smoothing, and by properly choosing the restriction and prolongation pair. In order to get a fixed linear preconditioner, one avoids using nonlinear smoothing, restriction, prolongation, or coarse solves. The positive definiteness is obtained by performing enough (in practice, even one may be enough), and an equal number of, pre- and post-smoothing steps; see, e.g., [5].

If smoothing is unbalanced, e.g., there is one step of pre-smoothing, but no post-smoothing, the multigrid preconditioner becomes nonsymmetric. Traditional assumptions of the standard convergence theory of iterative solvers are no longer valid, and convergence behavior may be unpredictable. The main goal of this paper is to describe our numerical experience experimenting with the influence of unbalanced smoothing in practical geometric multigrid preconditioning, specifically, the Semicoarsening Multigrid (SMG) method, see [13], provided by the parallel software package *hypr* [1].

We numerically analyze the possibility of turning off post-smoothing in geometric multigrid when used as a preconditioner in iterative linear and eigenvalue solvers for the 3D Laplacian in *hypr*. We solve linear systems using two variants (standard and flexible, e.g., [6]) of the preconditioned conjugate gradient (PCG) and preconditioned steepest descent (PSD) methods. The standard PCG is already coded in *hypr*. We have written the codes of flexible PCG and PSD by modifying the *hypr* standard PCG function. The eigenvalue problems are solved using the locally optimal block preconditioned conjugate gradient (LOBPCG) method, readily available in *hypr* through BLOPEX [2].

We observe that turning off the post-smoothing in SMG dramatically slows down the standard PCG-SMG. However, for the flexible PCG and LOBPCG, our numerical tests show that post-smoothing can be avoided. In the latter case, turning off the post-smoothing in SMG results in overall acceleration, due to the high costs of smoothing and relatively insignificant decrease in convergence speed. Our ob-

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to publish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.

Copyright 20XX ACM X-XXXXX-XX-X/XX/XX ...\$15.00.

A preprint is available at <http://arxiv.org/abs/1212.6680>

servations are also generally applicable for algebraic multi-grid preconditioning for graph Laplacians, appearing, e.g., in computational photography problems, as well as in 3D mesh processing tasks [11].

A different case of non-standard preconditioning, specifically, *variable preconditioning*, in PCG is considered in our earlier work [8]. There, we also find a dramatic difference in convergence speed between the standard and flexible version of PCG. The better convergence behavior of the flexible PCG is explained in [8] by its *local optimality*, which guarantees its convergence with at least the speed of PSD. Our numerical tests there show that, in fact, the convergence of PSD and the flexible PCG is practically very close. We perform the same comparison here, and obtain a similar result. We demonstrate for linear systems that PSD-SMG converges almost as fast as the flexible PCG-SMG if SMG post-smoothing is off in both methods.

Our numerical experiments are executed in both a strictly shared memory environment and in a distributed memory environment. Different size problems and with different shapes of the bricks are solved in our shared versus distributed tests, so the results are not directly comparable with each other. Our motivation to test both shared and distributed cases is to investigate how the effect of acceleration depends on the memory interconnection speed.

The rest of the paper is organized as follows. We formally describe the PSD and PCG methods used here for testing, and explain their differences. We briefly discuss the SMG preconditioning in *hypre* and present our numerical results for linear systems. One section is dedicated to eigenvalue problems. Our last section contains the relevant theory.

2. PSD AND PCG METHODS

For a general exposition of PSD and PCG, let SPD matrices A and T , and vectors b and x_0 be given, and denote $r_k = b - Ax_k$. Algorithm 1 is described in [8]

Algorithm 1: PSD and PCG methods

```

1 for  $k = 0, 1, \dots$  do
2    $s_k = Tr_k$ 
3   if  $k = 0$  then
4      $p_0 = s_0$ 
5   else
6      $p_k = s_k + \beta_k p_{k-1}$  (where  $\beta_k$  is either (1) or (2)
   for all iterations)
7   end
8    $\alpha_k = \frac{(s_k, r_k)}{(p_k, Ap_k)}$ 
9    $x_{k+1} = x_k + \alpha_k p_k$ 
10   $r_{k+1} = r_k - \alpha_k Ap_k$ 
11 end

```

Various methods are obtained by using different formulas for the scalar β_k . We set $\beta_k = 0$ for PSD,

$$\beta_k = \frac{(s_k, r_k)}{(s_{k-1}, r_{k-1})} \quad (1)$$

for the standard PCG, or

$$\beta_k = \frac{(s_k, r_k - r_{k-1})}{(s_{k-1}, r_{k-1})} \quad (2)$$

for the flexible PCG.

We note that in using (2), we are merely subtracting one term, (s_k, r_{k-1}) , in the numerator of (1), which appears in the standard CG algorithm. If T is a fixed SPD matrix, this term actually vanishes; see, e.g., [8]. By using (2) in a computer code, it is required that an extra vector be allocated to either calculate $r_k - r_{k-1}$ or store $-\alpha_k Ap_k$, compared to (1). The associated costs may be noticeable for large problems solved on parallel computers. Next, we numerically evaluate the extra costs by comparing the standard and flexible PCG with no preconditioning for a variety of problem sizes.

Our model problem used for all calculations in the present paper is for the three-dimensional negative Laplacian in a brick with homogeneous Dirichlet boundary conditions approximated by the standard finite difference scheme using the 7-point stencil with the grid size one in all three directions. The initial approximation is (pseudo)random. We simply call a code, called *struct*, which is provided in *hypre* to test SMG, with different command-line options.

To generate the data to compare iterative methods, we execute the following command,

```
mpexec -np 16 ./struct -n $n $n $n -solver 19
```

for the shared memory experiments and

```
mpexec -np 384 ./struct -n $n $n $n -solver 19
```

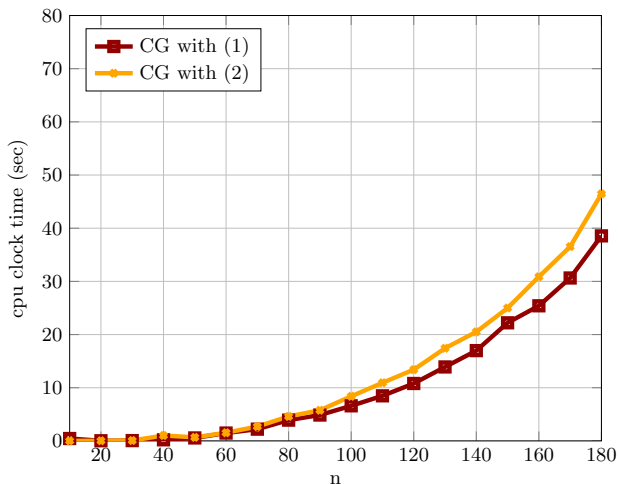
for the distributed memory experiments, where $\$n$ runs from 10 to 180, and determines the number of grid points in each of the three directions *per processor*. The size of the brick here is $\$np$ -times- $\$n$ -by- $\$n$ -by- $\$n$, i.e., the brick gets longer in the first direction with the increase in the number of cores. For example, using the largest value $\$n=180$, the maximum problem size we solve is 16x180-by-180-by-180=93,312,000 unknowns for $\$np=16$ and 384x180-by-180-by-180=2,239,488,000 unknowns for $\$np=384$. The option *-solver 19* tells the driver *struct* to use no preconditioning. The MPI option *-np 16* means that we run on 16 cores and we restrict to using only one node for the shared memory whereas for distributed memory we use 16 cores on 24 nodes with the MPI option *-np 384*. In fact, all our tests in this paper are performed on either 16 cores on one node or 16 cores on each of the 24 nodes, so in the rest of the paper we always omit the “*mpexec -np 16(384)*” part of the execution command for brevity.

Our comprehensive studies are performed on a 24 node cluster where each node is a dual-socket octo-core machine based on an Intel Xeon E5-2670 Sandy Bridge processor running at 2.60 GHz with 64 GB RAM of shared memory per node. Switched communications fabric between the nodes is provided by an InfiniBand 4X QDR Interconnect. Each experiment is performed using 16 cores on one node using shared memory and also using 16 cores on all 24 nodes via distributed memory.

In Figure 1, for the CG method without preconditioning we see a 20-25% cost overhead incurred due to the extra storage and calculation for the flexible variant, (2), relative to the standard variant, (1). Note that in each instance of the problem, the number of iterations of the CG method is the same regardless if either (1) or (2) is used for β_k .

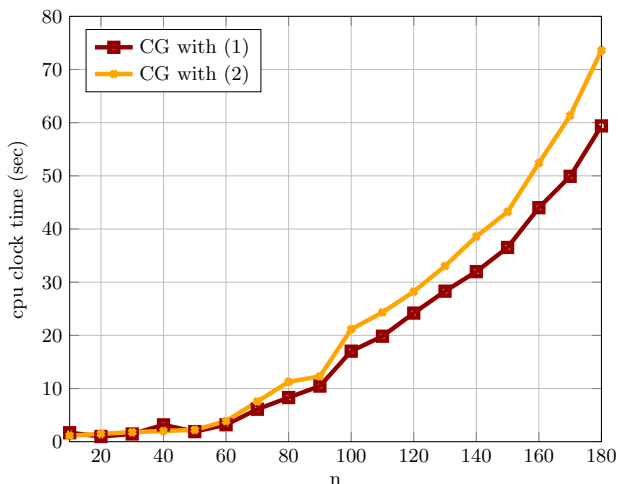
From Figure 1 one observes that the distributed memory (DM) case is not perfectly scalable, as there is about a 50% increase when the size of the problem is increased 24 times, proportionally to the number of processors. The same com-

Timing results of SD and CG
(16 processors on 1 node)



(a) Shared memory

Timing results of SD and CG
(16 processors each on 24 nodes)



(b) Distributed memory

Figure 1: Timing of unpreconditioned CG using (1) and (2).

parison actually holds for all other (a) and (b) figures up to Figure 8.

In Figure 2 we see, as expected without preconditioning, that the relative final residuals for both CG algorithms are identical, and that the SD algorithm of course performs much worse than either. The number of iterative steps is capped by 100, so most of Figure 2 shows the residual after 100 iterations, except for a small straight part of the CG line for $n=10,20,30$, where the iterations have converged.

3. PRECONDITIONING WITH SMG

In order to help overcome the slow convergence of the CG method, as observed in Figure 2, it is customary to introduce preconditioning. Here, we use the SMG solver as a preconditioner, provided by *hypr*. The SMG solver/preconditioner uses plane-relaxation as a smoother at each level in the V-cycle [1]. The number of pre- and post-relaxation

Final residual error of SD and CG
(16 processors on 1 node)

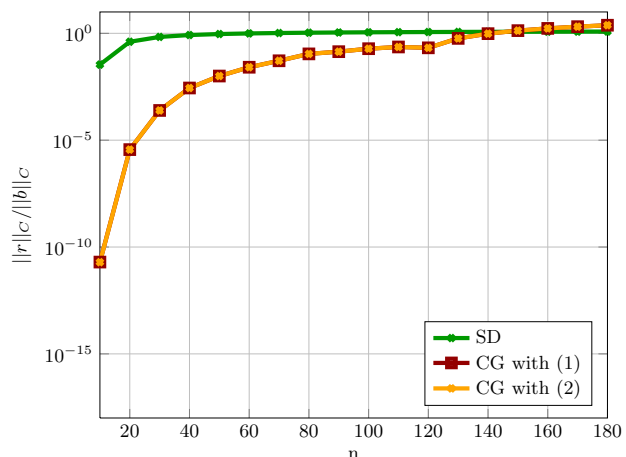


Figure 2: Accuracy comparison of SD and CG using (1) and (2).

smoothing steps is controlled by a command line parameter in the *struct* test driver. The data in Figures 3 and 4 is obtained by

```
./struct -n $n $n $n -solver 10 -v 1 1
```

in which the *-solver 10* option refers to the SMG preconditioning, and the number of pre- and post-relaxation smoothing steps is specified by the *-v* flag—one step each of pre- and post-relaxation in this call.

Although using (2) introduces some extra overhead, in the case of the SMG preconditioning, this is negligible as can be seen in Figure 3, since the SMG preconditioning, first, is relatively expensive computationally and, second, makes the PCG converge much faster, see Figure 4, compared to the non-preconditioned case displayed in Figure 2. As in Figure 2, for each instance of the PCG method, the number of iterations is equal as depicted in Figure 4. The PSD method performs a bit worse (only 2-3 more iterations) than either variant of PCG and not nearly as much worse as in Figure 2, which clearly indicates the high quality of the SMG preconditioner for these problems.

Using the same number of pre- and post-relaxation steps creates a symmetric preconditioner, in this test, an SPD preconditioner. Thus both PCG-SMG, (1) and (2), are expected to generate identical (up to round-off errors) iterative approximations. We indeed observe this effect in Figure 4, where the data points for the PCG-SMG with (1) and (2) are indistinguishable.

If no post-relaxation is performed within the SMG preconditioner, the convergence of the standard PCG method, i.e., with (1), is significantly slowed down, almost to the level where preconditioning is useless. The command used for this comparison is:

```
./struct -n 80 80 80 -solver 10 -v 1 0
```

in which the unbalanced relaxation is specified by the *-v* flag and the grid is 1280x80x80. In Figure 5, we compare convergence of PCG-SMG using (1) and (2) and PSD-SMG, where the SMG preconditioner has no post-relaxation. In PCG-SMG using (2) without post-relaxation of the SMG

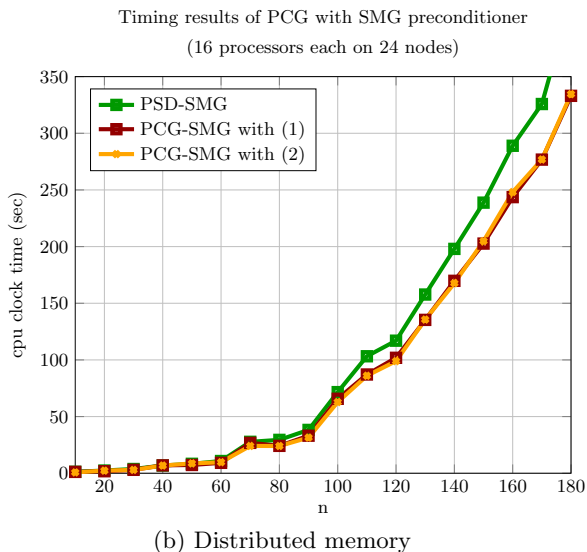
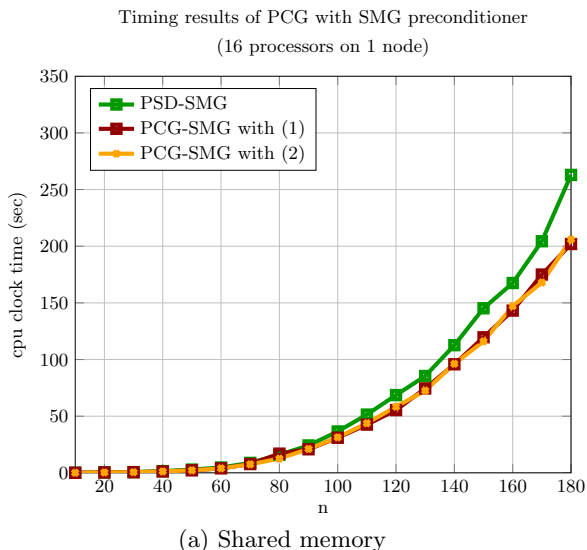


Figure 3: Cost for storage and calculation in PCG-SMG with (1) or (2)

preconditioner, we still achieve a very good convergence rate, as well as for PSD-SMG.

The convergence behavior in Figure 5 is similar to that observed in [8]. There, a variable SPD preconditioner makes the standard PCG, i.e., using (1), almost stall, while the convergence rates of PSD and flexible PCG, i.e., with (2), are good and close to each other.

However, the SMG preconditioner is fixed and linear, according to its description in [13] and our numerical verification, so the theoretical explanation of such a convergence behavior in [8] is not directly applicable here. Moreover, turning off the post-relaxation smoothing in a multigrid preconditioner makes it nonsymmetric—the case not theoretically covered in [8], where the assumption is always made that the preconditioner is SPD.

We add the data for the absence of post-relaxation (option $-v\ 1\ 0$) in the SMG preconditioner to Figures 3 and 4 to obtain Figures 6 and 7. The number of iterations of the solver does increase a bit for both (2) and for the PSD method

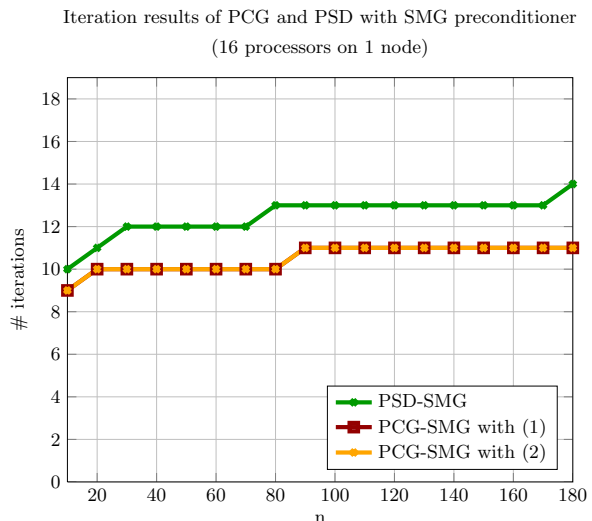


Figure 4: Iteration count for PSD-SMG and PCG-SMG with (1) or (2)

with no post-relaxation in the SMG preconditioner, but not enough to outweigh the cost savings of not using the post-relaxation in the SMG preconditioner. The overall improvement is 43% for all problems tested.

4. PRECONDITIONING OF LOBPCG WITH SMG

The LOBPCG method [7] computes the m smallest eigenvalues of a linear operator and is implemented within *hypr* through BLOPEX; see [2]. We conclude our numerical experiments with a comparison of the use of balanced and unbalanced relaxation in the SMG preconditioner for the LOBPCG method with $m = 1$.

In these tests, the matrix remains the same as in the previous section, i.e., corresponds to the three-dimensional negative Laplacian in a brick with homogeneous Dirichlet boundary conditions approximated by the standard finite difference scheme using the 7-point stencil with the grid size of one in all three directions. But in this section we compute the smallest eigenvalue and the corresponding eigenvector, rather than solve a linear system. The initial approximation to the eigenvector is (pseudo)random.

We generate the data for Figures 8 and 9 with the commands:

```
./struct -n $n $n $n -solver 10 -lobpcg -v 1 0
./struct -n $n $n $n -solver 10 -lobpcg -v 1 1
```

where $\$n$ runs from 10 to 120. We also use the $-P$ option in *struct* to make the brick more even-sided. In the shared memory experiment we use $-P\ 4\ 2\ 2$ which will create a $4n$ -by- $2n$ -by- $2n$ brick and in the distributed case we use $-P\ 8\ 8\ 6$ which will create an $8n$ -by- $8n$ -by- $6n$ brick.

For this experiment, as seen in Figure 9, the number of LOBPCG iterations for the non-balanced SMG preconditioner is roughly 50% more than that for the balanced SMG preconditioner. However, the cost savings, which is about 30-50%, of not using the post-relaxation in the SMG preconditioner outweigh the higher number of iterations, as shown in Figure 8, and thus justify turning off the post-relaxation

Iteration error of PCG and PSD with SMG preconditioner
(16 processors on 1 node)

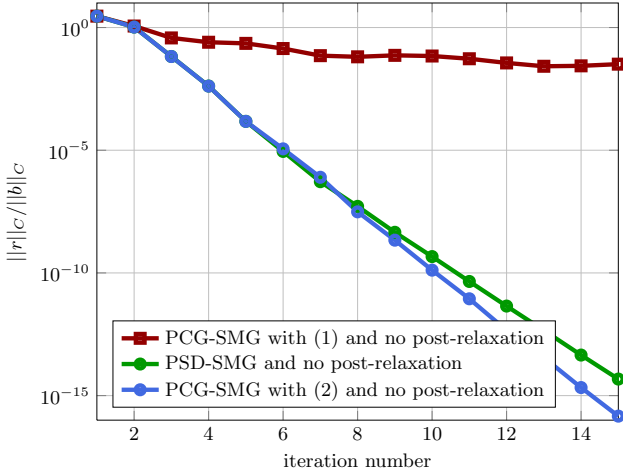


Figure 5: Iteration Error for PCG-SMG and PSD-SMG

in this case. From Figure 8 one observes that the distributed memory case is not perfectly scalable, as there is about a 50% increase when the size of the problem is increased 24 times, proportionally to the number of processors. Finally, we note that the existing LOBPCG convergence theory in [7, 10] requires an SPD preconditioner T , and does not explain convergence if T is nonsymmetric.

5. THEORETICAL JUSTIFICATION OF THE OBSERVED NUMERICAL BEHAVIOR

For linear systems with SPD coefficient matrices, the use of nonsymmetric preconditioning has been justified, e.g., in [3, Section 12.3], [4, 12], and [14, Section 10.2]. The arguments used there are applicable for nonsymmetric and variable preconditioning.

Specifically, it is shown in [14, Section 10.2] that the flexible PCG, i.e., using (2), is locally optimal, i.e., on every step it converges not slower than PSD. The convergence rate bound for the PSD with nonsymmetric preconditioning established in [14, Section 10.2] is

$$\|r_{k+1}\|_{A^{-1}} \leq \delta \|r_k\|_{A^{-1}}, \quad (3)$$

under the assumption

$$\|I - AT\|_{A^{-1}} \leq \delta < 1, \quad (4)$$

where $\|\cdot\|_{A^{-1}}$ denotes the operator norm induced by the corresponding vector norm $\|x\|_{A^{-1}} = \sqrt{x' A^{-1} x}$.

The key identity for PSD, that easily leads to bound (3), is presented in the following theorem.

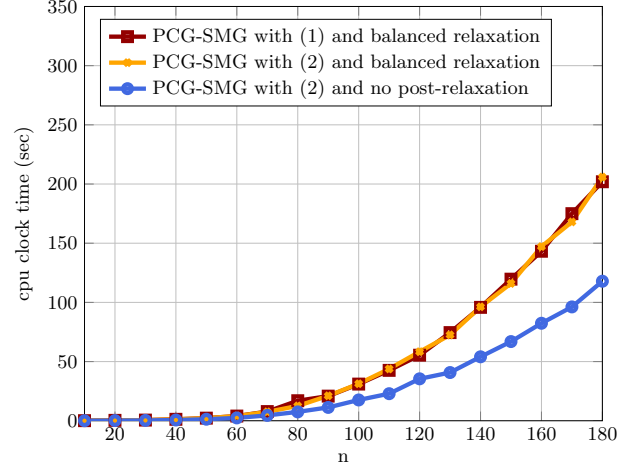
THEOREM 1. *The identity holds,*

$$\|r_{k+1}\|_{A^{-1}} / \|r_k\|_{A^{-1}} = \sin(\angle_{A^{-1}}\{r_k, ATr_k\}), \quad (5)$$

where the right-hand side is defined via

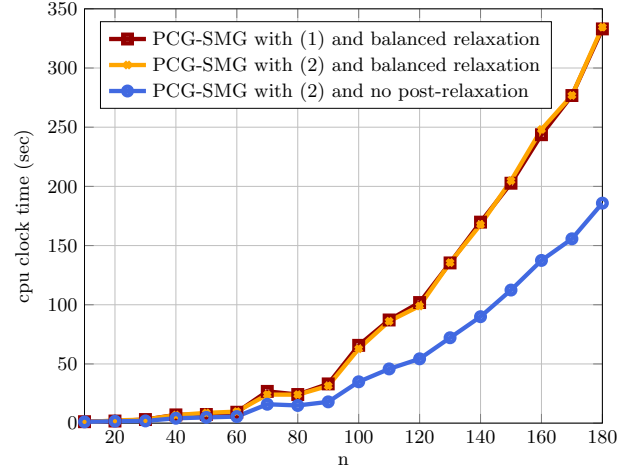
$$\cos(\angle_{A^{-1}}\{r_k, ATr_k\}) = \frac{|(r_k)' T r_k|}{\|r_k\|_{A^{-1}} \|ATr_k\|_{A^{-1}}}.$$

Timing results of PCG with SMG preconditioner
(16 processors on 1 node)



(a) Shared memory

Timing results of PCG with SMG preconditioner
(16 processors each on 24 nodes)



(b) Distributed memory

Figure 6: Cost comparison of relaxation in PCG-SMG using (1) or (2)

PROOF. Identity (5) is actually proved, although not explicitly formulated, in the proof of [14, Theorem 10.2]. Alternatively, identity (5) is equivalent to

$$\|e_{k+1}\|_A / \|e_k\|_A = \sin(\angle_A\{e_k, T A e_k\}), \quad (6)$$

where $A e_k = r_k$, which is the statement of [8, Lemma 4.1]. We note that [8] generally assumes that the preconditioner T is SPD, but this assumption is not actually used in the proof of [8, Lemma 4.1]. \square

Assumption (4) is very simple, but has one significant drawback—it does not allow arbitrary scaling of the preconditioner T , while the PCG and PSD methods are invariant with respect to scaling of T . The way around it is to scale the preconditioner T before assumption (4) is verified. We now illustrate such a scaling under an additional assumption that T is SPD, following [8]. We start with a theorem,

Iteration results of PCG and PSD with SMG preconditioner
(16 processors on 1 node)

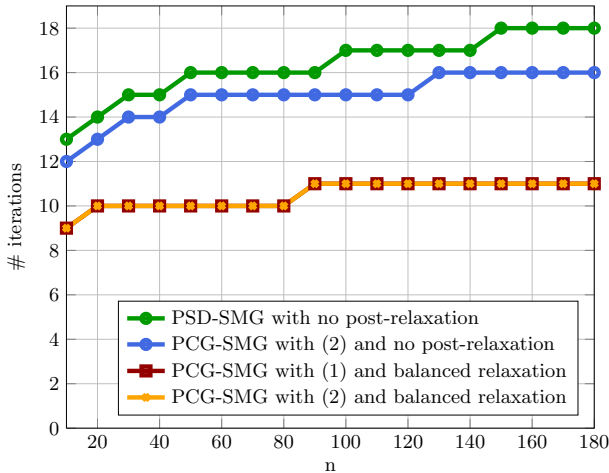


Figure 7: Iteration count for PSD-SMG and PCG-SMG using (1) or (2)

connecting assumption (4) with its equivalent, and probably more traditional form.

THEOREM 2. *Let the preconditioner T be SPD. Then assumption (4) is equivalent to*

$$\|I - TA\|_{T^{-1}} \leq \delta < 1. \quad (7)$$

PROOF. Since T is SPD, on the one hand, the matrix product AT is also SPD, but with respect to the A^{-1} scalar product. This implies that assumption (4) is equivalent to the statement that $\Lambda(AT) \in [1 - \delta, 1 + \delta]$ with $\delta < 1$, where $\Lambda(\cdot)$ denotes the matrix spectrum. On the other hand, the matrix product TA is SPD as well, with respect to the T^{-1} scalar product. Thus, assumption (7) is equivalent to the statement that $\Lambda(TA) \in [1 - \delta, 1 + \delta]$. This means the equivalence of assumptions (4) and (7), since $\Lambda(AT) = \Lambda(TA)$. \square

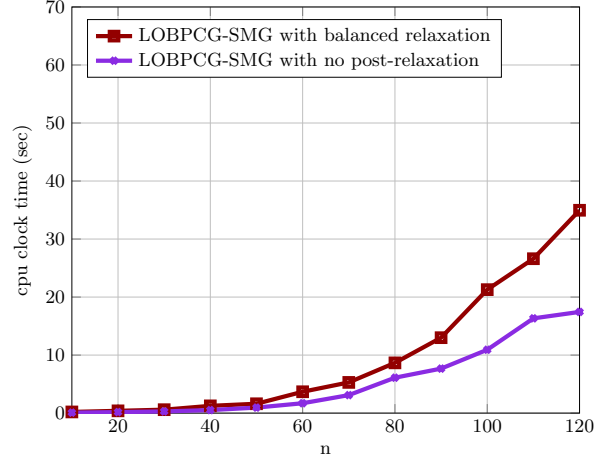
Let us now, without loss of generality, as in [9, p. 96] and [8, pp. 1268–1269], always scale the SPD preconditioner T in such a way that

$$\max\{\Lambda(TA)\} + \min\{\Lambda(TA)\} = 2.$$

Then we have $\delta = (\kappa(TA) - 1)/(\kappa(TA) + 1)$ and, vice versa, $\kappa(TA) = (1 + \delta)/(1 - \delta)$, where $\kappa(\cdot)$ denotes the matrix spectral condition number. The convergence rate bound (3) for the PSD with nonsymmetric preconditioning in this case turns into the standard PSD convergence rate bound for the case of SPD preconditioner T ; see. e.g., [8, Bound (1.3)]. Moreover, [8, Theorem 5.1] shows that this convergence rate bound is sharp for PSD, and cannot be improved for flexible PCG, i.e., using (2), if the SPD preconditioner T changes on every iteration. The latter result naturally extends to the case of nonsymmetric preconditioning of [14, Section 10.2].

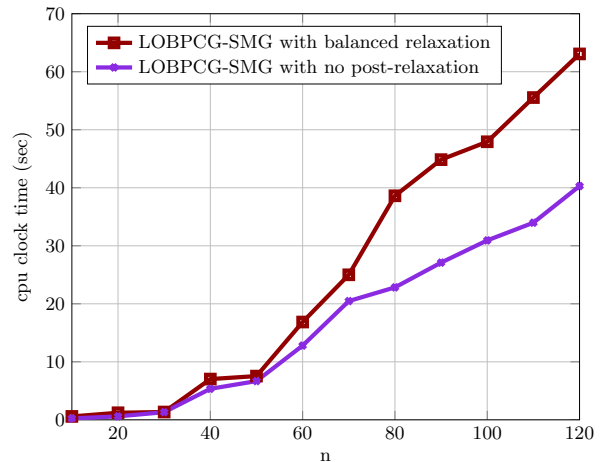
Compared to linear systems, eigenvalue problems are significantly more complex. Sharp convergence rate bounds for symmetric eigenvalue problems have been obtained in the last decade, and only for the simplest preconditioned method; see [9, 10] and references therein. A possibility of using nonsymmetric preconditioning for symmetric eigen-

Timing of LOBPCG-SMG with and without balanced relaxation
(16 Processors on 1 node)



(a) Shared memory

Timing of LOBPCG-SMG with and without balanced relaxation
(16 processors each on 24 nodes)



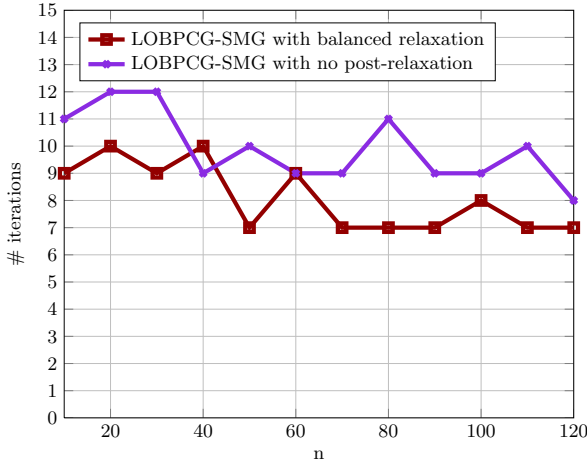
(b) Distributed memory

Figure 8: Cost for higher relaxation level for LOBPCG-SMG

value problems has not been considered before, to our knowledge. However, our check of arguments of [9] and preceding works, where a PSD convergence rate bound is proved assuming (4) and SPD preconditioning, reveals that the latter assumption, SPD, is actually never significantly used, and can be dropped without affecting the bound.

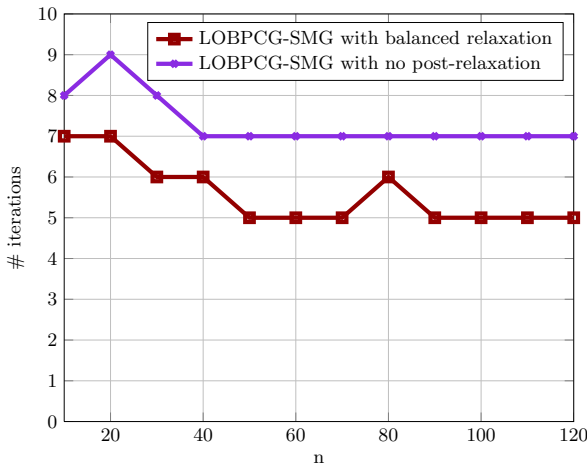
The arguments above lead us to a surprising determination that whether or not the preconditioner is SPD is of no importance for PSD convergence, given the same quality of preconditioning, measured by (4) after preconditioner prescaling. If the preconditioner is fixed SPD then the standard PCG is the method of choice. The cases, where the preconditioner is variable or nonsymmetric, are similar to each other—the standard non-flexible PCG, i.e., using (1), stalls, while the flexible PCG converges, due to its local optimality, but may not be much faster compared to PSD. This explains the numerical results using nonsymmetric preconditioning reported in this work, as related to results of [8] for variable SPD preconditioning.

Iteration count of LOBPCG-SMG with and without balanced relaxation
(16 Processors on 1 node)



(a) Shared memory

Iteration count of LOBPCG-SMG with and without balanced relaxation
(16 processors each on 24 nodes)



(b) Distributed memory

Figure 9: Iteration comparison of relaxation levels for LOBPCG-SMG

6. CONCLUSION

Although the flexible PCG linear solver does require a bit more computational effort and storage as compared to the standard PCG, within the scope of preconditioning the extra effort can be worthwhile, if the preconditioner is not fixed SPD. Moreover, our numerical tests showed that the behavior is similar in both shared and distributed memory. Thus our conclusion is that the effect of acceleration is independent of the speed of the memory interconnection. The use of geometric multigrid without post-relaxation is demonstrated to be surprisingly efficient as a preconditioner for locally optimal iterative methods, such as the flexible PCG for linear systems and LOBPCG for eigenvalue problems.

7. ACKNOWLEDGMENT

The authors would like to thank Rob Falgout, Van Henson, Panayot Vassilevski, and other members of the *hypre*

team for their attention to our numerical results reported here and the Center for Computational Mathematics University of Colorado Denver for the use of the cluster. This work is partially supported by NSF awards CNS 0958354 and DMS 1115734.

8. REFERENCES

- [1] *HYPRE User's Manual*. Center for Applied Scientific Computing, Lawrence Livermore National Lab, 2012.
- [2] M. E. Argentati, I. Lashuk, A. V. Knyazev, and E. E. Ovtchinnikov. Block locally optimal preconditioned eigenvalue Solvers (BLOPEX) in HYPRE and PETSC. *SIAM J. Sci. Comput.*, 29(4):2224–2239, 2007.
- [3] O. Axelsson. *Iterative solution methods*. Cambridge University Press, Cambridge, 1994.
- [4] R. Blaheta. GPCG-generalized preconditioned CG method and its use with non-linear and non-symmetric displacement decomposition preconditioners. *Numer. Linear Algebra Appl.*, 9(6-7):527–550, 2002.
- [5] J. H. Bramble and X. Zhang. The analysis of multigrid methods. In P. Ciarlet and J. Lions, editors, *Solution of Equation in R^n (Part 3), Techniques of Scientific Computing*, volume 7 of *Handbook of Numerical Analysis*, pages 173–415. Elsevier, 2000.
- [6] G. H. Golub and Q. Ye. Inexact preconditioned conjugate gradient method with inner-outer iteration. *SIAM J. Sci. Comput.*, 21(4):1305–1320, 1999.
- [7] A. V. Knyazev. Toward the optimal preconditioned eigensolver: Locally optimal block preconditioned conjugate gradient method. *SIAM J. Sci. Comput.*, 23(2):517–541, 2001.
- [8] A. V. Knyazev and I. Lashuk. Steepest descent and conjugate gradient methods with variable preconditioning. *SIAM J. Matrix Anal. Appl.*, 29(4):1267–1280, 2007.
- [9] A. V. Knyazev and K. Neymeyr. A geometric theory for preconditioned inverse iteration. III. A short and sharp convergence estimate for generalized eigenvalue problems. *Linear Algebra Appl.*, 358:95–114, 2003.
- [10] A. V. Knyazev and K. Neymeyr. Gradient flow approach to geometric convergence analysis of preconditioned eigensolvers. *SIAM J. Matrix Anal. Appl.*, 31(2):621–628, 2009.
- [11] D. Krishnan, R. Fattal, and R. Szeliski. Efficient Preconditioning of Laplacian Matrices for Computer Graphics. In *ACM Transactions on Graphics (Proc. SIGGRAPH 2013)*, volume 32(4). ACM SIGGRAPH, July 2013.
- [12] Y. Notay. Flexible conjugate gradients. *SIAM J. Sci. Comput.*, 22(4):1444–1460 (electronic), 2000.
- [13] S. Schaffer. A semicoarsening multigrid method for elliptic partial differential equations with highly discontinuous and anisotropic coefficients. *SIAM J. Sci. Comput.*, 20(1):228–242, 1998.
- [14] P. S. Vassilevski. *Multilevel block factorization preconditioners*. Springer, New York, 2008.