

Preconditioning Techniques for Saddle Point Problems

Michele Benzi

Department of Mathematics and Computer Science
Emory University
Atlanta, GA

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Outline

1 The challenge

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- 2 The Augmented Lagrangian (AL) approach

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- 3 The modified Augmented Lagrangian-based preconditioner

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The need for efficient and robust solvers

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Research in this area is still very much ongoing!

Results for Kay, Loghin and Wathen preconditioner

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Uniform FEM discretizations: isoP2-P0 and isoP2-P1. These discretizations satisfy the inf-sup condition: no pressure stabilization is needed. SUPG stabilization is used for the velocities.

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A preconditioning step requires two convection-diffusion solves (three in 3D) and one Poisson solve at each iteration, plus some mat-vecs.

Results for Kay, Loghin, and Wathen preconditioner (cont.)

Results for KLV preconditioner.

mesh size h	viscosity ν				
	1	10^{-1}	10^{-2}	10^{-3}	10^{-4}
constant wind					
1/16	6 / 12	8 / 16	12 / 24	30 / 34	100 / 80
1/32	6 / 10	10 / 16	14 / 24	24 / 28	86 / 92
1/64	6 / 10	8 / 14	16 / 24	22 / 32	64 / 66
1/128	6 / 10	8 / 12	16 / 26	24 / 36	64 / 58
rotating vortex					
1/16	6 / 8	10 / 12	30 / 40	> 400 / 188	
1/32	6 / 8	10 / 12	30 / 40	> 400 / 378	
1/64	4 / 6	8 / 12	26 / 40	> 400 / > 400	
1/128	4 / 6	8 / 10	22 / 44	228 / > 400	

Number of Bi-CGSTAB iterations

(Note: exact solves used throughout. Stopping criterion: $\|\mathbf{b} - \mathcal{A}\mathbf{x}_k\|_2 < 10^{-6}\|\mathbf{b}\|_2$).

Results with Vanka-type MG preconditioner

Results for Vanka-MG-BiCGStab approach, isoP2-P0 FEM.

mesh size h	viscosity = ν				
	1	10^{-1}	10^{-2}	10^{-3}	10^{-4}
constant wind					
1/16	4	4	3	4	5
1/32	4	4	3	4	4
1/64	4	4	4	3	5
1/128	4	4	4	3	4
rotating vortex					
1/16	4	5	5	8	14
1/32	4	4	6	9	17
1/64	4	4	5	8	40
1/128	4	4	4	9	> 400

Better than KLU preconditioner, but still not robust for low viscosity. Can we do better than this?

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Augmented Lagrangian formulation of saddle point problems

Consider the equivalent **augmented Lagrangian formulation** (Fortin, Glowinski, 1982) given by

$$\begin{pmatrix} A + \gamma B^T W^{-1} B & B^T \\ B & O \end{pmatrix} \begin{pmatrix} u \\ p \end{pmatrix} = \begin{pmatrix} f + \gamma B^T W^{-1} g \\ g \end{pmatrix}, \quad (1)$$

where $\gamma > 0$ and W is symmetric positive definite.

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Letting $A_\gamma := A + \gamma B^T W^{-1} B$ and $f_\gamma := f + \gamma B^T W^{-1} g$,

$$\begin{pmatrix} A_\gamma & B^T \\ B & O \end{pmatrix} \begin{pmatrix} u \\ p \end{pmatrix} = \begin{pmatrix} f_\gamma \\ g \end{pmatrix}, \quad \text{or} \quad \hat{\mathcal{A}} \mathbf{x} = \hat{\mathbf{b}}. \quad (2)$$

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B. and Olshanskii (SISC 2006) introduced the following block preconditioner for (2)

$$\mathcal{P} = \begin{pmatrix} A_\gamma & B^T \\ O & \widehat{S} \end{pmatrix}, \quad \widehat{S}^{-1} = -\nu \widehat{M}_p^{-1} - \gamma W^{-1}. \quad (3)$$

Analysis for the Oseen problem

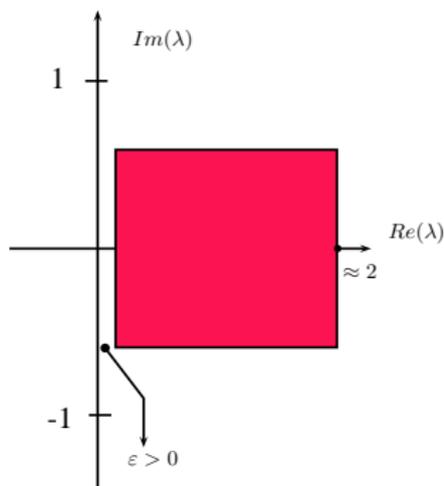
Theorem (B./Olshanskii, SISC 2006)

Setting $W = M_p$, the preconditioned matrix $\mathcal{P}^{-1}\hat{A}$ has the eigenvalue 1 of multiplicity n ; the remaining m eigenvalues are contained in a rectangle in the right half plane with sides independent of the mesh size h , and bounded away from 0. Moreover, for $\gamma = O(\nu^{-1})$ the rectangle does not depend on ν . When $\gamma \rightarrow \infty$, all the eigenvalues tend to 1.

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Analysis for the Oseen problem (cont.)

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For $\nu < 1$, if $\gamma = \|(BA^{-1}B^T)^{-1}M_p\|_{M_p}$ the residual norms in GMRES with the original AL preconditioner satisfy

$$\|\hat{\mathbf{b}} - \hat{\mathbf{A}}\mathbf{x}_k\| \leq q^k \|\hat{\mathbf{b}} - \hat{\mathbf{A}}\mathbf{x}_0\|,$$

where $q < 1$ is independent of problem parameters h , ν and α .

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Recall that the field of values of an $n \times n$ matrix \mathcal{B} is the subset of \mathbf{C} defined by

$$\mathcal{F}(\mathcal{B}) := \{\mathbf{x}^* \mathcal{B} \mathbf{x} \mid \mathbf{x} \in \mathbf{C}^n, \mathbf{x}^* \mathbf{x} = 1\}.$$

We proved that $\mathcal{F}(\mathcal{P}^{-1}\mathcal{A})$ is bounded and bounded away from 0 for all h , ν and α . This implies the above convergence result for GMRES.

Practical considerations

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- In practice we use $W = \widehat{M}_p = \text{diag}(M_p)$ in A_γ
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Though the previous theorems suggest that $\gamma = O(\nu^{-1})$, in practice, $\gamma = O(1)$ is sufficient for (near) parameter-independent convergence.

The multigrid solver for A_γ

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Let $\mathbf{V}_h, \mathbf{Q}_h$ denote the finite element velocity and pressure fine spaces. Also, let $P_h : L_0^2(\Omega) \rightarrow \mathbf{Q}_h$ be the orthogonal projection. Consider the bilinear form

$$a_h(\mathbf{u}, \mathbf{v}) = \nu \langle \nabla \mathbf{u}, \nabla \mathbf{v} \rangle + \langle P_h \operatorname{div} \mathbf{u}, \operatorname{div} \mathbf{v} \rangle.$$

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Let $\tilde{\mathbf{V}}_h \subset \mathbf{V}_h$ and $\tilde{\mathbf{Q}}_h \subset \mathbf{Q}_h$ denote subspaces such that there is a constant c independent of h with

$$\inf_{\tilde{\mathbf{q}}_h \in \tilde{\mathbf{Q}}_h} \sup_{\tilde{\mathbf{v}}_h \in \tilde{\mathbf{V}}_h} \frac{\langle \tilde{\mathbf{q}}_h, \operatorname{div} \tilde{\mathbf{v}}_h \rangle}{\|\nabla \tilde{\mathbf{v}}_h\| \|\tilde{\mathbf{q}}_h\|} \geq c > 0$$

and $\tilde{\mathbf{V}}_h \subset \ker(P_H \operatorname{div})$.

The multigrid solver for A_γ (cont.)

For given $\tilde{\mathbf{u}}_H \in \tilde{\mathbf{V}}_H$ (coarse space), let $\tilde{\mathbf{u}}_h$ be the solution of the problem

$$a_h(\tilde{\mathbf{u}}_h, \tilde{\mathbf{v}}_h) = a_h(\mathbf{u}_H, \tilde{\mathbf{v}}_h) \quad \forall \tilde{\mathbf{v}}_h \in \tilde{\mathbf{V}}_h. \quad (4)$$

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For an appropriate choice of $\tilde{\mathbf{V}}_h, \tilde{\mathbf{Q}}_h$, solving (4) requires solving N_p independent linear systems of dimension 6 (in 2D) or 9 (in 3D) where N_p is the number of elements in the coarse grid triangulation T_H .

The multigrid solver for A_γ (cont.)

For example, for isoP2-P0 or P2-P0 finite elements we can take

$$\begin{aligned}\tilde{\mathbf{Q}}_h &= \left\{ \tilde{\mathbf{q}}_h \in \mathbf{Q}_h : \int_{\tau} \tilde{\mathbf{q}}_h \, dx = 0 \quad \forall \tau \in T_H \right\}, \\ \tilde{\mathbf{V}}_h &= \left\{ \tilde{\mathbf{v}}_h \in \mathbf{V}_h : \tilde{\mathbf{v}}_h|_{\partial\tau} = 0 \quad \forall \tau \in T_H \right\}.\end{aligned}$$

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For the restriction, we simply take the L^2 -orthogonal projection from \mathbf{V}_h to \mathbf{V}_H .

Finally, the smoother is chosen so as to effectively eliminate the oscillatory components in $\ker(P_h \operatorname{div})$. We use a multiplicative Schwarz-type iteration with overlapping blocks, where each block contains degrees of freedom supporting a basis function from $\ker(P_h \operatorname{div})$.

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See B. and Olshanskii (SISC, 2006) for additional details.

Numerical results

Table: Bi-CGSTAB iterations (isoP2-P0 FEM, SUPG, $\gamma = 1$)

Viscosity ν	1	10^{-1}	10^{-2}	10^{-3}	10^{-4}
Mesh size	Constant wind				
1/16	7	5	5	6	6
1/32	7	5	6	7	8
1/64	5	5	6	5	7
1/128	5	5	5	5	6
Mesh size	Rotating vortex				
1/16	5	5	6	10	15
1/32	4	4	5	10	21
1/64	4	4	5	9	18
1/128	4	5	5	7	14

The rate of convergence of Krylov subspace method with this preconditioner is nearly optimal:

- Independent of the grid; almost independent of viscosity
- Cost is $O(n + m)$ per iteration
- Similar results with isoP2-P1 FEM

Numerical results (cont.)

Results for AL approach, isoP2-P1 FEM.

mesh size h	viscosity ν				
	1.	10^{-1}	10^{-2}	10^{-3}	10^{-4}
	parameter γ				
	1.	1.	1.	0.1	0.02
constant wind					
1/16	6	6	7	8	24
1/32	7	6	10	8	22
1/64	7	6	8	7	19
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rotating vortex					
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Number of preconditioned BiCGStab iterations
 (\hat{A}_γ^{-1} is one $W(1,1)$ -cycle).

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$$A_\gamma = A + \gamma B^T W^{-1} B = \begin{pmatrix} A_1 + \gamma B_1^T W^{-1} B_1 & \gamma B_1^T W^{-1} B_2 \\ \gamma B_2^T W^{-1} B_1 & A_2 + \gamma B_2^T W^{-1} B_2 \end{pmatrix} := \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix}.$$

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The **modified AL preconditioner** (B., Olshanskii and Wang, IJNMF 2011) is defined as

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- $A_{ii} = A_i + \gamma B_i^T W^{-1} B_i$ ($i = 1, 2$) can be interpreted as discrete scalar anisotropic convection-diffusion operators with anisotropy ratio $\approx 1 + \frac{\gamma}{\nu}$.

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- $A_{ii} = A_i + \gamma B_i^T W^{-1} B_i$ ($i = 1, 2$) can be interpreted as discrete scalar anisotropic convection-diffusion operators with anisotropy ratio $\approx 1 + \frac{\gamma}{\nu}$.
- They can be solved with standard algebraic multigrid (AMG) methods, in particular, parallel AMG solvers.

Analysis

Note that

$$\widehat{\mathcal{A}}\widetilde{\mathcal{P}}^{-1} = \left(\begin{array}{c|cc} I_{n/2} & O & O \\ * & I_{n/2} - D & E \\ * & F & I_m - G \end{array} \right).$$

The eigenvalues of $\widehat{\mathcal{A}}\widetilde{\mathcal{P}}^{-1}$ are $\lambda = 1$ of multiplicity $n/2$, plus the eigenvalues of

$$\begin{pmatrix} I_{n/2} - D & E \\ F & I_m - G \end{pmatrix} = I_{n/2+m} - \begin{pmatrix} D & -E \\ -F & G \end{pmatrix}.$$

In general, the multiplicity of $\lambda = 1$ is only $n/2$.

Analysis

Note that

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However, letting $\widehat{S}^{-1} = -\gamma W^{-1}$, the matrix on the right-hand side is rank deficient by $n/2$, so $\widehat{\mathcal{A}}\widetilde{\mathcal{P}}^{-1}$ has the eigenvalue $\lambda = 1$ of multiplicity at least n .

Using [field of values](#) analysis, we can prove that the convergence rate of GMRES with the modified AL preconditioner is h -independent, with a moderate dependence on ν .

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- 2 'discretize' the gradient and divergence by one-sided differences;
- 3 note that $W = \widehat{M}_p$ scales as h^2 ;
- 4 express $\widetilde{\mathcal{P}}$ and \widehat{A} in terms of "Fourier eigenvalues", and find the γ that minimizes the average distance of the non-unit eigenvalues $\lambda(\gamma)$ of the preconditioned matrix $\widehat{A}\widetilde{\mathcal{P}}^{-1}$ from 1.

Note that γ only depends on h and ν . Hence it can be pre-computed, so no overhead is imposed. The discretizations are [symbolic](#).

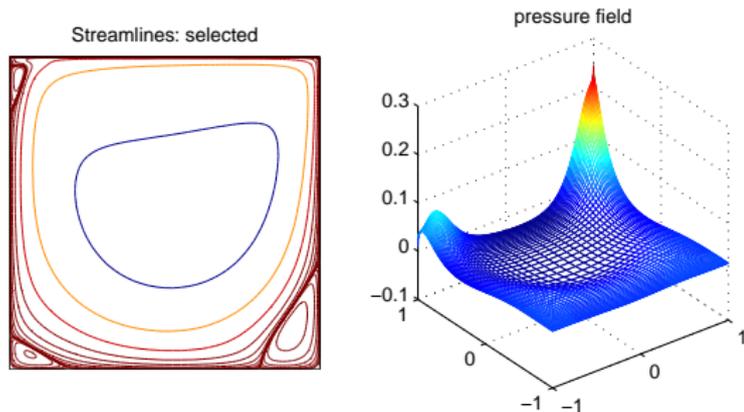
Details in B. and Wang (SISC, 2011).

Example: a regularized lid driven cavity problem

All 2D experiments are done using IFISS package (Elman, Silvester & Ramage).

In the lid driven cavity problem, the flow is enclosed in a square with $u_1 = 1 - x^4$, $u_2 = 0$ on the top to represent the moving lid.

Figure: Regularized lid driven cavity (Q2-Q1, $\nu = 0.001$, stretched 128×128 grid)



Iteration counts for the lid driven cavity problem

Table: GMRES iterations with modified AL preconditioner (cavity, Q2-Q1, uniform grids)

Viscosity	0.1		0.01		0.005		0.001	
Grid	LFA	Opt	LFA	Opt	LFA	Opt	LFA	Opt
16×16	9	9	12	12	26	15	42	23
32×32	10	9	11	11	20	14	37	29
64×64	9	9	11	10	13	13	33	27
128×128	9	9	10	10	13	12	25	24

Observations:

- The number of GMRES iterations with γ chosen by LFA is almost the same as for the optimal γ , especially on the finest grid
- The iteration counts with both sets of γ are independent of grid size and only mildly dependent on viscosity

Values of γ

Table: The values of γ chosen by LFA and optimal values (cavity, Q2-Q1, uniform grids)

Viscosity	0.1		0.01		0.005		0.001	
	LFA	Opt	LFA	Opt	LFA	Opt	LFA	Opt
16 × 16	0.42	0.45	0.075	0.085	0.270	0.068	0.220	0.063
32 × 32	0.29	0.38	0.056	0.050	0.098	0.043	0.067	0.035
64 × 64	0.32	0.32	0.055	0.045	0.032	0.032	0.037	0.022
128 × 128	0.28	0.28	0.036	0.046	0.022	0.032	0.020	0.017

Eigenvalues of preconditioned matrices

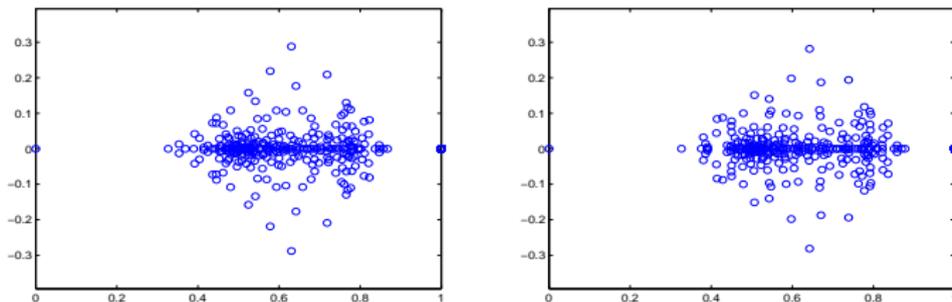


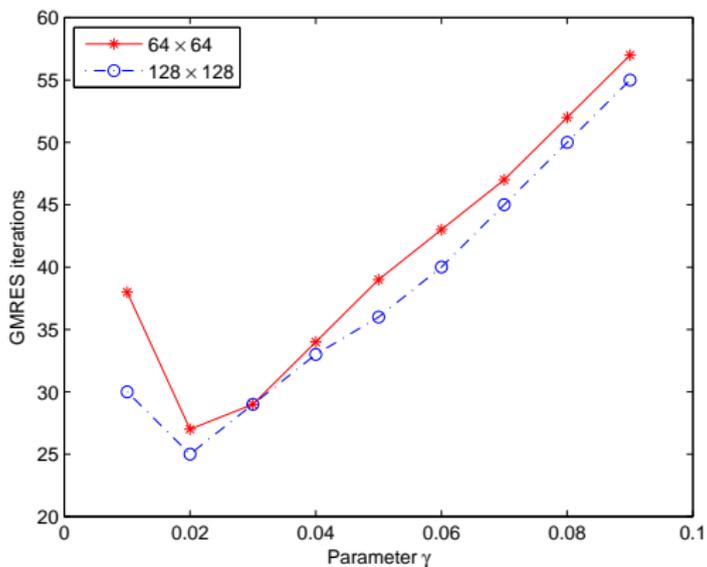
Figure: Plots of the eigenvalues of the preconditioned Oseen matrix (lid driven cavity, Q2-Q1, 32×32 uniform grid, $\nu = 0.01$). Left: with optimal γ . Right: with γ chosen by Fourier analysis.

The two values of γ are very close: 0.050 vs. 0.056.

The eigenvalue $\lambda = 1$ has multiplicity n (for all γ).

Iteration counts with various values of γ

Figure: GMRES iterations with modified AL preconditioner (cavity, Q2-Q1, uniform grids, $\nu = 0.001$)



Iteration counts with Newton linearization

Use the same values of γ as for Picard linearization.

Table: GMRES iterations with modified AL preconditioner (cavity, Q2-Q1, stretched grids, Newton)

Viscosity	0.1		0.01		0.005		0.001	
Grid	LFA	Opt	LFA	Opt	LFA	Opt	LFA	Opt
16×16	13	13	21	21	20	25	99	62
32×32	14	14	23	23	31	30	71	60
64×64	14	14	24	23	35	33	84	72
128×128	15	14	26	23	40	34	95	82

Not quite h -independent for small ν .

Results for stretched grids and comparison with PCD/LSC/mPCD

Table: GMRES with modified AL preconditioner (cavity, Q2-Q1, stretched grids)

Viscosity	0.1		0.01		0.005		0.001	
Grid	FA	Opt	FA	Opt	FA	Opt	FA	Opt
16×16	9	9	11	11	21	13	35	20
32×32	9	9	11	11	17	14	31	23
64×64	8	8	11	11	14	14	29	25
128×128	8	7	11	11	14	13	26	26

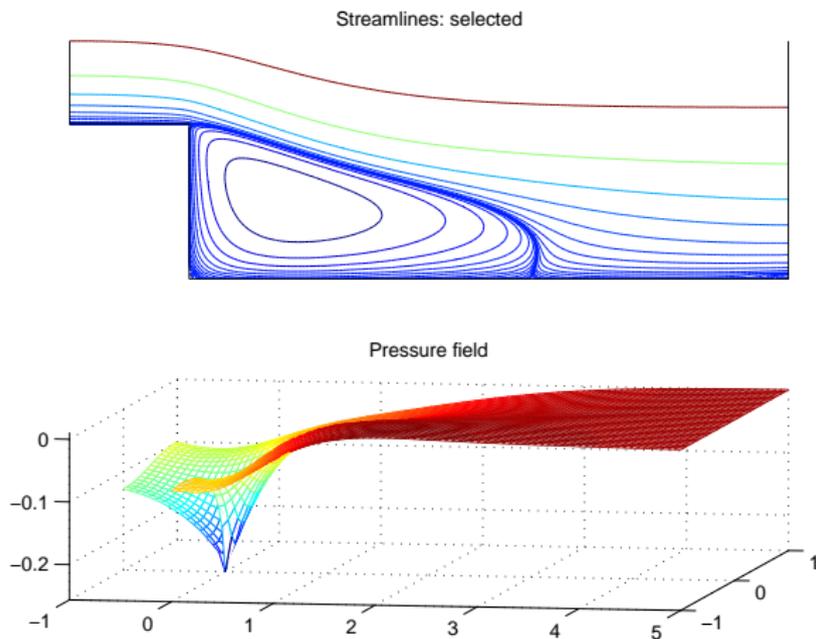
Table: GMRES iterations with PCD, LSC and mPCD preconditioners of Elman, Silvester, Wathen (cavity, Q2-Q1, stretched grids, $\nu = 0.001$)

Grid	PCD	LSC	mPCD
16×16	79	50	81
32×32	105	78	201
64×64	117	117	135
128×128	117	174	144

Note: All methods have similar costs per iteration.

A backward facing step test problem

Figure: Backward facing step problem (Q2-Q1, $\nu = 0.005$, uniform 64×192 grid)



Iteration counts for the backward facing step problem

Table: GMRES iterations with modified AL preconditioner (step, Q2-Q1, uniform grids)

Viscosity	0.1		0.01		0.005	
	LFA	Opt	LFA	Opt	LFA	Opt
16 × 48	15	12	46	16	59	19
32 × 96	12	12	24	17	38	20
64 × 192	12	11	17	16	26	19
128 × 384	11	11	15	15	19	19

Comparison of exact and inexact solves

In the following Table we present a comparison of modified AL preconditioning with **exact** and **inexact** inversion of diagonal blocks A_{ij} .

For the 'exact' solves we use the sparse LU factorization with column AMD reordering available in Matlab.

For the inexact solves we use **one iteration** (V-cycle) of AMG using the HSL_M120 code developed by Boyle, Mihajlovic and Scott (IJNME 2010).

We perform tests for both Picard and Newton linearizations of the lid driven cavity problem discretized with Q2-Q1 elements (Newton is harder), using the same value of γ from Fourier analysis in both cases. The viscosity is $\nu = 0.005$.

The experiments are performed in Matlab 7.9.0 on a Sun Microsystems SunFire.

The upshot:

- Using inexact solves does not affect the convergence rates
- Inexact solves result in much faster solution times

Iteration counts and timings of exact solve and AMG (MI20)

Table: Comparison of exact and inexact inner solvers. GMRES iterations and timings with modified AL preconditioner (cavity, Q2-Q1, uniform grids, $\nu = 0.005$)

Grid	Picard		Newton	
	Exact	MI20	Exact	MI20
Timings				
64×64	13	13	35	36
Set-up time	1.93	0.31	1.95	0.26
Iter time	0.62	2.76	1.75	5.76
Total time	2.55	3.07	3.70	6.02
128×128	13	13	39	39
Setup time	34.90	1.29	34.34	1.25
Iter time	4.44	12.00	10.94	29.38
Total time	39.34	13.29	45.28	30.63
256×256	13	13	43	43
Setup time	856.74	5.86	673.29	6.07
Iter time	40.22	58.84	85.84	152.05
Total time	896.96	64.70	759.12	158.12

The modified AL preconditioner for 3D problems

For 3D Oseen problems $A = \text{diag}(A_1, A_2, A_3)$ and $B = (B_1, B_2, B_3)$.

$$\begin{aligned}
 A_\gamma &= A + \gamma B^T W^{-1} B \\
 &= \begin{pmatrix} A_1 & O & O \\ O & A_2 & O \\ O & O & A_3 \end{pmatrix} + \gamma \begin{pmatrix} B_1^T \\ B_2^T \\ B_3^T \end{pmatrix} W^{-1} (B_1 \quad B_2 \quad B_3) \\
 &= \begin{pmatrix} A_1 + \gamma B_1^T W^{-1} B_1 & \gamma B_1^T W^{-1} B_2 & \gamma B_1^T W^{-1} B_3 \\ \gamma B_2^T W^{-1} B_1 & A_2 + \gamma B_2^T W^{-1} B_2 & \gamma B_2^T W^{-1} B_3 \\ \gamma B_3^T W^{-1} B_1 & \gamma B_3^T W^{-1} B_2 & A_3 + \gamma B_3^T W^{-1} B_3 \end{pmatrix} \\
 &=: \begin{pmatrix} A_{11} & A_{12} & A_{13} \\ A_{21} & A_{22} & A_{23} \\ A_{31} & A_{32} & A_{33} \end{pmatrix},
 \end{aligned}$$

so the modified AL preconditioner is

$$\tilde{P} = \begin{pmatrix} \tilde{A}_\gamma & B^T \\ O & \hat{S} \end{pmatrix} = \begin{pmatrix} A_{11} & A_{12} & A_{13} & B_1^T \\ O & A_{22} & A_{23} & B_2^T \\ O & O & A_{33} & B_3^T \\ O & O & O & \hat{S} \end{pmatrix}.$$

Parallel results

These preliminary runs are done on a cluster at ORNL. The cluster consists of eighty Cray XK6 nodes, and each node has a 16-core AMD 2.2 GHz 6274 Opteron processor and 32 GB of GDDR3 RAM.

The subproblems in the modified AL preconditioner are solved inexactly by one AMG iteration ('ML' solver in Trilinos).

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No. of cores	2	4	8	16	32	64
Iterations	29	28	28	25	26	30
Set-up time	2.04	1.18	0.67	0.43	0.31	0.25
Iter time	7.11	4.00	1.87	0.78	0.43	0.34
Total time	10.15	5.18	2.54	1.21	0.74	0.59

Parallel results (cont.)

3D enclosed flow problem, $\nu = 0.01$, Marker-and-Cell discretization.

- 1,036,288 DOFs on $64 \times 64 \times 64$ grid
- 8,442,624 DOFs on $128 \times 128 \times 128$ grid.

No. of cores	2	4	8	16	32	64
$64 \times 64 \times 64$	23	22	22	23	24	27
Set-up time	4.12	2.53	1.42	0.91	0.79	0.96
Iter time	11.20	6.51	3.06	1.56	0.98	0.89
Total time	15.32	9.04	4.48	2.47	1.77	1.85
$128 \times 128 \times 128$	26	26	26	26	28	32
Set-up time	36.78	20.89	11.36	6.43	3.86	3.04
Iter time	115.12	78.00	39.42	19.35	10.05	6.09
Total time	151.90	101.37	54.44	25.78	13.91	9.13

Parallel results (cont.)

3D driven cavity, $\nu = 0.05$, P2-P1 discretization. Grad-div stabilization already present in the formulation of the NSE.

No. of cores	2	4	8	16	32	64
$16 \times 16 \times 16$	28	26	25	24	23	23
Set-up time	1.31	1.09	1.06	0.75	0.55	0.42
Iter time	3.46	2.18	1.44	0.82	0.54	0.41
Total time	4.77	3.27	2.50	1.57	1.09	0.83
$24 \times 24 \times 24$	26	24	24	23	24	22
Set-up time	4.63	3.92	3.81	2.37	1.64	1.10
Iter time	11.82	7.65	5.30	2.81	1.79	1.06
Total time	16.45	11.57	9.11	5.18	3.43	2.16
$32 \times 32 \times 32$	24	22	21	22	21	20
Set-up time	11.31	9.75	9.46	5.70	3.55	2.44
Iter time	26.48	17.38	11.44	6.64	3.79	2.11
Total time	37.78	27.13	20.90	12.34	7.34	4.55

Note: The Trilinos set-up does not scale for a small number of cores.

Outline

- 1 The challenge
- 2 The Augmented Lagrangian (AL) approach
- 3 The modified Augmented Lagrangian-based preconditioner
- 4 Conclusions**

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- Current and future work: implementation using the Teko framework in Trilinos; application to real problems.

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