Implementation and numerical stability of saddle point solvers

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Recent developments in the solution of indefinite systems

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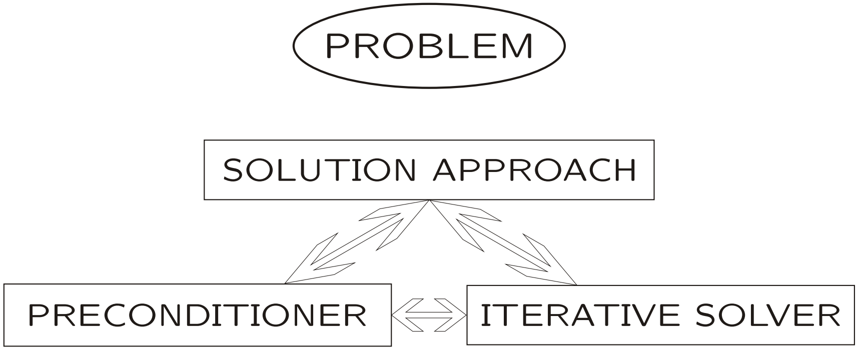
Saddle point problems

We consider a saddle point problem with the symmetric 2×2 block form

$$\begin{pmatrix} A & B \\ B^T & 0 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} f \\ 0 \end{pmatrix}.$$

- A is a square $n \times n$ nonsingular (symmetric positive definite) matrix,
- B is a rectangular $n \times m$ matrix of (full column) rank m.

Applications: mixed finite element approximations, weighted least squares, constrained optimization, computational fluid dynamics, electromagnetism etc. [Benzi, Golub and Liesen, 2005], [Elman, Silvester, Wathen, 2005]. For the updated list of applications leading to saddle point problems contact [Benzi].


PROBLEM
SOLUTION APPROACH
PRECONDITIONER
ITERATIVE SOLVER

Iterative solution of saddle point problems

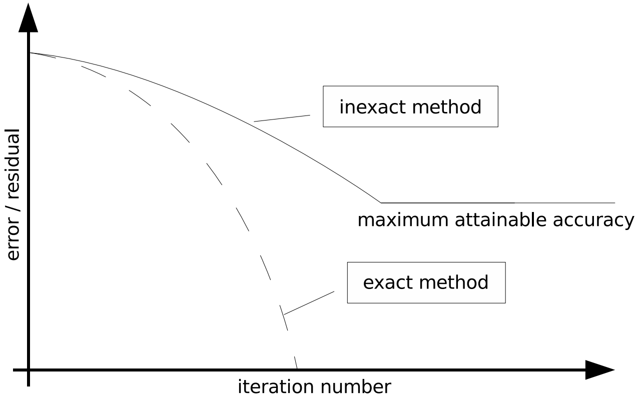
1. **segregated approach**: outer iteration for solving the reduced Schur complement or null-space projected system;
2. **coupled approach with block preconditioning**: iteration scheme for solving the preconditioned system;
3. **rounding errors in floating point arithmetic**: numerical stability of the solver

Numerous solution schemes: inexact Uzawa algorithms, inexact null-space methods, inner-outer iteration methods, two-stage iteration processes, multilevel or multigrid methods, domain decomposition methods

Numerous preconditioning techniques and schemes: block diagonal preconditioners, block triangular preconditioners, constraint preconditioning, Hermitian/skew-Hermitian preconditioning and other splittings, combination preconditioning

Numerous iterative solvers: conjugate gradient (CG) method, MINRES, GMRES, flexible GMRES, GCR, BiCG, BiCGSTAB, ...

Delay of convergence and limit on the final accuracy



Numerical experiments: a small model example

$$A = \mathrm{tridiag}(1,4,1) \in \mathbb{R}^{100\times 100},\ B = \mathrm{rand}(100,20),\ f = \mathrm{rand}(100,1),$$

$$\kappa(A) = \|A\| \cdot \|A^{-1}\| = 5.9990 \cdot 0.4998 \approx 2.9983,$$

$$\kappa(B) = \|B\| \cdot \|B^{\dagger}\| = 7.1695 \cdot 0.4603 \approx 3.3001.$$

Schur complement reduction method

- Compute y as a solution of the Schur complement system

$$B^T A^{-1} B y = B^T A^{-1} f,$$

- compute x as a solution of

$$Ax = f - By.$$

- Segregated vs. coupled approach: x_k and y_k approximate solutions to x and y, respectively.
- Inexact solution of systems with A: **every computed solution $\hat{u}$ of $Au = b$ is interpreted as an exact solution of a perturbed system**

$$(A + \Delta A)\hat{u} = b + \Delta b, \ \|\Delta A\| \leq \tau \|A\|, \ \|\Delta b\| \leq \tau \|b\|, \ \tau \kappa(A) \ll 1.$$

Iterative solution of the Schur complement system

$$\left.\begin{array}{l}
\text{choose } y_0,\ \text{solve } Ax_0 = f - By_0 \\
\text{compute } \alpha_k \text{ and } p_k^{(y)} \\
y_{k+1} = y_k + \alpha_k p_k^{(y)} \\
\quad \left|\begin{array}{l}
\text{solve } Ap_k^{(x)} = -Bp_k^{(y)} \\
\color{red}{\text{back-substitution:}} \\
\textbf{A: } x_{k+1} = x_k + \alpha_k p_k^{(x)}, \\
\textbf{B: } \text{solve } Ax_{k+1} = f - By_{k+1}, \\
\textbf{C: } \text{solve } Au_k = f - Ax_k - By_{k+1}, \\
\qquad x_{k+1} = x_k + u_k.
\end{array}\right\} \begin{array}{l}\text{inner}\\ \text{iteration}\end{array} \\
r_{k+1}^{(y)} = r_k^{(y)} - \alpha_k B^T p_k^{(x)}
\end{array}\right\} \begin{array}{l}\text{outer}\\ \text{iteration}\end{array}$$

Accuracy in the saddle point system

$$\|f - Ax_k - By_k\| \le \frac{O(\alpha_1)\kappa(A)}{1 - \tau\kappa(A)}(\|f\| + \|B\|Y_k),$$

$$\|-B^T x_k - r_k^{(y)}\| \le \frac{O(\alpha_2)\kappa(A)}{1 - \tau\kappa(A)}\|A^{-1}\|\|B\|(\|f\| + \|B\|Y_k),$$

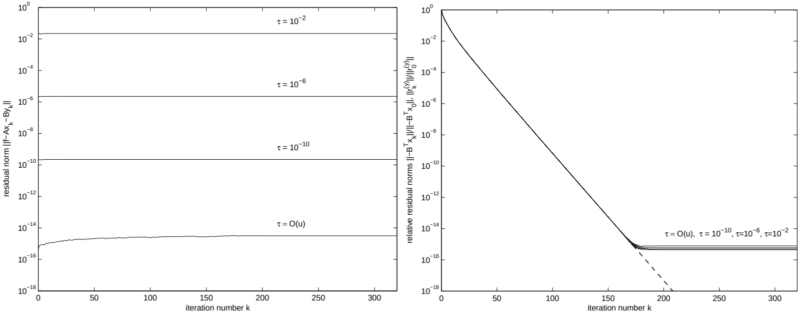
$$Y_k \equiv \max\{\|y_i\| \mid i = 0, 1, \dots, k\}.$$

Back-substitution scheme	α_1	α_2
A: Generic update $x_{k+1} = x_k + \alpha_k p_k^{(x)}$	τ	u
B: Direct substitution $x_{k+1} = A^{-1}(f - By_{k+1})$	τ	τ
C: Corrected dir. subst. $x_{k+1} = x_k + A^{-1}(f - Ax_k - By_{k+1})$	u	τ

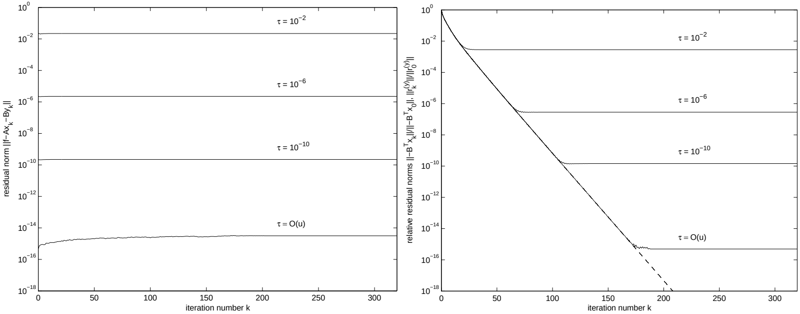
additional system with A

$$-B^T A^{-1} f + B^T A^{-1} B y_k = -B^T x_k - B^T A^{-1}(f - Ax_k - By_k)$$

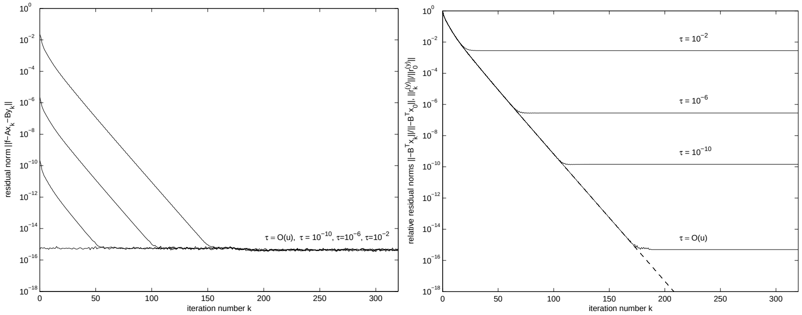
Generic update: $x_{k+1} = x_k + \alpha_k p_k^{(x)}$



Direct substitution: $x_{k+1} = A^{-1}(f - By_{k+1})$



Corrected direct substitution: $x_{k+1} = x_k + A^{-1}(f - Ax_k - By_{k+1})$



Null-space projection method

- compute $x \in N(B^T)$ as a solution of the projected system
$$(I - \Pi)A(I - \Pi)x = (I - \Pi)f,$$
- compute y as a solution of the least squares problem
$$By \approx f - Ax,$$
$\Pi = B(B^TB)^{-1}B^T$ is the orthogonal projector onto $R(B)$.
- Schemes with the inexact solution of least squares with B. Every computed approximate solution $\bar{v}$ of a least squares problem $Bv \approx c$ is interpreted as an exact solution of a perturbed least squares
$$(B + \Delta B)\bar{v} \approx c + \Delta c, \ \|\Delta B\| \leq \tau\|B\|, \ \|\Delta c\| \leq \tau\|c\|, \ \tau\kappa(B) \ll 1.$$

Null-space projection method

$$
\left.\begin{array}{l}
\text{choose } x_0, \ \text{solve } By_0 \approx f - Ax_0 \\[6pt]
\text{compute } \alpha_k \text{ and } p_k^{(x)} \in N(B^T) \\[6pt]
x_{k+1} = x_k + \alpha_k p_k^{(x)} \\[6pt]
\qquad \left.\begin{array}{|l}
\text{solve } Bp_k^{(y)} \approx r_k^{(x)} - \alpha_k A p_k^{(x)} \\[4pt]
\textcolor{red}{\text{back-substitution:}} \\[4pt]
\textbf{A: } y_{k+1} = y_k + p_k^{(y)}, \\[4pt]
\textbf{B: } \text{solve } By_{k+1} \approx f - Ax_{k+1}, \\[4pt]
\textbf{C: } \text{solve } Bv_k \approx f - Ax_{k+1} - By_k, \\[4pt]
\qquad y_{k+1} = y_k + v_k.
\end{array}\right\} \begin{array}{l}\text{inner}\\ \text{iteration}\end{array} \\[6pt]
r_{k+1}^{(x)} = r_k^{(x)} - \alpha_k A p_k^{(x)} - B p_k^{(y)}
\end{array}\right\} \begin{array}{l}\text{outer}\\ \text{iteration}\end{array}
$$

Accuracy in the saddle point system

$$\|f - Ax_k - By_k - r_k^{(x)}\| \leq \frac{O(\alpha_3)\kappa(B)}{1-\tau\kappa(B)}(\|f\| + \|A\|X_k),$$

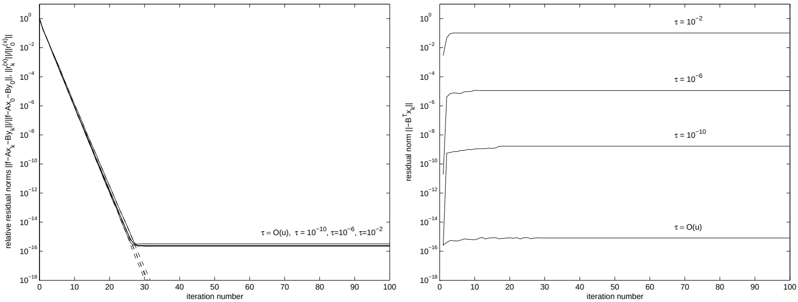
$$\|-B^T x_k\| \leq \frac{O(\tau)\kappa(B)}{1-\tau\kappa(B)}\|B\|X_k,$$

$$X_k \equiv \max\{\|x_i\| \mid i = 0, 1, \ldots, k\}.$$

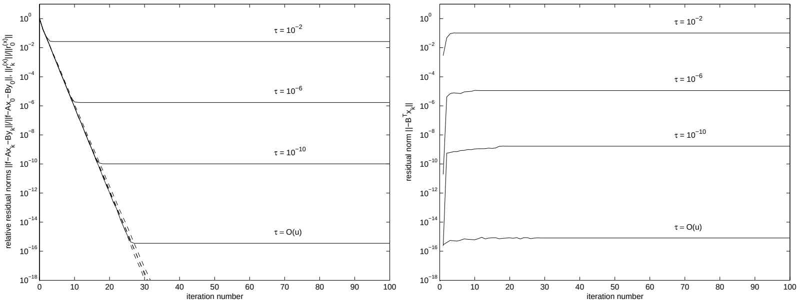
Back-substitution scheme		α_3
A:	Generic update $y_{k+1} = y_k + p_k^{(y)}$	u
B:	Direct substitution $y_{k+1} = B^\dagger(f - Ax_{k+1})$	τ
C:	Corrected dir. subst. $y_{k+1} = y_k + B^\dagger(f - Ax_{k+1} - By_k)$	u

additional least square with B

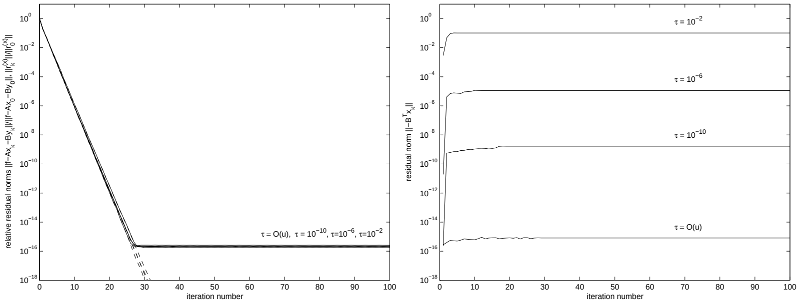
Generic update: $y_{k+1} = y_k + p_k^{(y)}$



Direct substitution: $y_{k+1} = B^{\dagger}(f - Ax_{k+1})$



Corrected direct substitution: $y_{k+1} = y_k + B^{\dagger}(f - Ax_{k+1} - By_k)$



Stationary iterative methods

- $\mathcal{A} = \mathcal{A}x = b$, $\mathcal{M} - \mathcal{N}$

- A: $\mathcal{M}x_{k+1} = \mathcal{N}x_k + b$

  B: $x_{k+1} = x_k + \mathcal{M}^{-1}(b - \mathcal{A}x_k)$

- Inexact solution of systems with $\mathcal{M}$: **every computed solution $\overline{y}$ of $\mathcal{M}y = z$ is interpreted as an exact solution of a perturbed system**

$$(\mathcal{M} + \Delta\mathcal{M})\overline{y} = z, \quad \|\Delta\mathcal{M}\| \leq \tau\|\mathcal{M}\|, \quad \tau k(\mathcal{M}) \ll 1$$

Accuracy of the computed approximate solution

A $\quad \mathcal{M}x_{k+1} = \mathcal{M}x_k + b$

$$\frac{\|\hat{x}_{k+1} - x\|_\infty}{\|x\|_\infty} \leq \tau \frac{\| \, |\mathcal{M}^{-1}| \, |\mathcal{M}| \, |x| \, \|_\infty}{\|x\|_\infty}$$

B $\quad x_{k+1} = x_k + \mathcal{M}^{-1}(b - \mathcal{A}x_k)$

$$\frac{\|\hat{x}_{k+1} - x\|_\infty}{\|x\|_\infty} \leq O(u) \frac{\| \, |\mathcal{M}^{-1}| \, |\mathcal{A}| \, |x| \, \|_\infty}{\|x\|_\infty}$$

new_value=old_value+small_correction

Two-stage iterative methods

$$\mathcal{M}_1 x_{k+1/2} = \mathcal{N}_1 x_k + b, \qquad \mathcal{A} = \mathcal{M}_1 - \mathcal{N}_1$$
$$\mathcal{M}_2 x_{k+1} = \mathcal{N}_2 x_{k+1/2} + b, \quad \mathcal{A} = \mathcal{M}_2 - \mathcal{N}_2$$

$$\begin{aligned}
x_{k+1/2} &= x_k + \mathcal{M}_1^{-1}(b - \mathcal{A}x_k) \\
x_{k+1} &= x_{k+1/2} + \mathcal{M}_2^{-1}(b - \mathcal{A}x_{k+1/2}) \\
&\Leftrightarrow \\
x_{k+1} &= x_k + (\mathcal{M}_1^{-1} + \mathcal{M}_2^{-1} - \mathcal{M}_2^{-1}\mathcal{A}\mathcal{M}_1^{-1})(b - \mathcal{A}x_k) \\
&= x_k + (\mathcal{I} + \mathcal{M}_2^{-1}\mathcal{N}_1)\mathcal{M}_1^{-1}(b - \mathcal{A}x_k) \\
&= x_k + \mathcal{M}_2^{-1}(\mathcal{I} + \mathcal{N}_2\mathcal{M}_1^{-1})(b - \mathcal{A}x_k)
\end{aligned}$$

$$\frac{\|\hat{x}_{k+1} - x\|_\infty}{\|x\|_\infty} \le O(u)\frac{\|\,|\mathcal{M}_2^{-1}(\mathcal{I} + \mathcal{N}_2\mathcal{M}_1^{-1})|\,|\mathcal{A}|\,|x|\,\|_\infty}{\|x\|_\infty}$$

$\mathcal{A}$ symmetric indefinite, $\mathcal{P}$ positive definite

$$\mathcal{A} = \begin{pmatrix} A & B \\ B^T & 0 \end{pmatrix} \approx \mathcal{P} = \mathcal{R}^T\mathcal{R}$$

$$\left(\mathcal{R}^{-T}\mathcal{A}\mathcal{R}^{-1}\right)\mathcal{R}\begin{pmatrix} x \\ y \end{pmatrix} = \mathcal{R}^{-T}\begin{pmatrix} f \\ 0 \end{pmatrix}$$

$\mathcal{R}^{-T}\mathcal{A}\mathcal{R}^{-1}$ is symmetric indefinite!

$\mathcal{P}$ symmetric indefinite or nonsymmetric

$$\mathcal{P}^{-1}\mathcal{A}\begin{pmatrix} x \\ y \end{pmatrix} = \mathcal{P}^{-1}\begin{pmatrix} f \\ 0 \end{pmatrix}$$

$$\left(\mathcal{A}\mathcal{P}^{-1}\right)\mathcal{P}\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} f \\ 0 \end{pmatrix}$$

$\mathcal{P}^{-1}\mathcal{A}$ and $\mathcal{A}\mathcal{P}^{-1}$ are nonsymmetric!

Schur complement approach with indefinite preconditioner

$$\begin{pmatrix} A & B \\ B^T & 0 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} f \\ 0 \end{pmatrix}, \quad \mathcal{P} = \begin{pmatrix} A & B \\ B^T & B^T A^{-1} B - I \end{pmatrix}$$

$$\mathcal{A}\mathcal{P}^{-1} = \begin{pmatrix} I & 0 \\ (I - S)B^T A^{-1} & S \end{pmatrix}$$

$S = B^T A^{-1} B$, $\mathcal{A}\mathcal{P}^{-1}$ **nonsymmetric** but **diagonalizable** and it has a 'nice' spectrum!

$$\sigma(\mathcal{A}\mathcal{P}^{-1}) \subset \{1\} \cup \sigma(B^T A^{-1} B^T)$$

[Durazzi, Ruggiero 2003], [Fortin, El-Maliki, 2009?]

Krylov method with the preconditioner: basic properties

$$\begin{pmatrix} x_0 \\ y_0 \end{pmatrix}, r_0 = \begin{pmatrix} 0 \\ s_0 \end{pmatrix}, e_{k+1} = \begin{pmatrix} x - x_{k+1} \\ y - y_{k+1} \end{pmatrix}$$

$$r_{k+1} = \begin{pmatrix} f \\ 0 \end{pmatrix} - \begin{pmatrix} A & B \\ B^T & 0 \end{pmatrix} \begin{pmatrix} x_{k+1} \\ y_{k+1} \end{pmatrix}$$

$$r_0 = \begin{pmatrix} 0 \\ s_0 \end{pmatrix} \Rightarrow r_{k+1} = \begin{pmatrix} 0 \\ s_{k+1} \end{pmatrix}$$
$$\Rightarrow Ax_{k+1} + By_{k+1} = f$$

Preconditioned CG method: saddle point problem and indefinite preconditioner

$$r_{k+1}^T \mathcal{P}^{-1} r_j = 0, \; j = 0, \dots, k$$

y_{k+1} is an iterate from CG applied to the Schur complement system

$$B^T A^{-1} B y = B^T A^{-1} f!$$

satisfying

$$\|y - y_{k+1}\|_{B^T A^{-1} B} = \min_{u \in x_0 + K_{k+1}(B^T A^{-1} B, B^T A^{-1} f)} \|y - u\|_{B^T A^{-1} B}$$

Preconditioned CG algorithm

$$\begin{pmatrix} x_0 \\ y_0 \end{pmatrix},\ r_0 = b - \mathcal{A}\begin{pmatrix} x_0 \\ y_0 \end{pmatrix} = \begin{pmatrix} 0 \\ s_0 \end{pmatrix}$$

$$\begin{pmatrix} p_0^{(x)} \\ p_0^{(y)} \end{pmatrix} = \mathcal{P}^{-1} r_0 = \mathcal{P}^{-1}\begin{pmatrix} 0 \\ s_0 \end{pmatrix}$$

$k = 0, 1, \ldots$

$$\alpha_k = \left(\begin{pmatrix} 0 \\ s_k \end{pmatrix}, \mathcal{P}^{-1}\begin{pmatrix} 0 \\ s_k \end{pmatrix}\right) / \left(\mathcal{A}\begin{pmatrix} p_k^{(x)} \\ p_k^{(y)} \end{pmatrix}, \begin{pmatrix} p_k^{(x)} \\ p_k^{(y)} \end{pmatrix}\right) \qquad \alpha_k = \frac{(r_k, z_k)}{(\mathcal{A}p_k, p_k)}$$

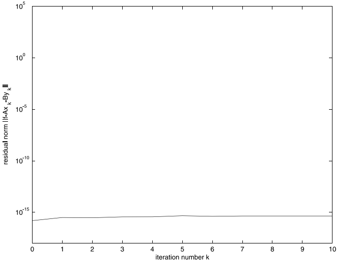
$$\begin{pmatrix} x_{k+1} \\ y_{k+1} \end{pmatrix} = \begin{pmatrix} x_k \\ y_k \end{pmatrix} + \alpha_k \begin{pmatrix} p_k^{(x)} \\ p_k^{(y)} \end{pmatrix}$$

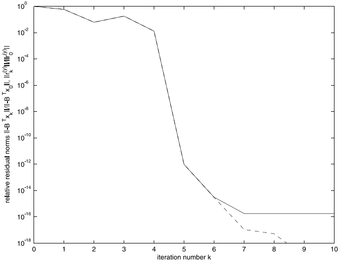
$$r_{k+1} = r_k - \alpha_k \mathcal{A}\begin{pmatrix} p_k^{(x)} \\ p_k^{(y)} \end{pmatrix} = \begin{pmatrix} 0 \\ s_{k+1} \end{pmatrix} \qquad z_{k+1} = \mathcal{P}^{-1} r_{k+1}$$

$$\beta_k = \left(\begin{pmatrix} 0 \\ s_{k+1} \end{pmatrix}, \mathcal{P}^{-1}\begin{pmatrix} 0 \\ s_{k+1} \end{pmatrix}\right) / \left(\begin{pmatrix} 0 \\ s_k \end{pmatrix}, \mathcal{P}^{-1}\begin{pmatrix} 0 \\ s_k \end{pmatrix}\right) \qquad \beta_k = \frac{(r_{k+1}, z_{k+1})}{(r_k, z_k)}$$

$$\begin{pmatrix} p_{k+1}^{(x)} \\ p_{k+1}^{(y)} \end{pmatrix} = \mathcal{P}^{-1}\begin{pmatrix} 0 \\ s_{k+1} \end{pmatrix} + \beta_k \begin{pmatrix} p_k^{(x)} \\ p_k^{(y)} \end{pmatrix} = \begin{pmatrix} -A^{-1} B p_{k+1}^{(y)} \\ p_{k+1}^{(y)} \end{pmatrix} \qquad p_{k+1} = z_{k+1} + \beta_k p_k$$

Generic update: $x_{k+1} = x_k + \alpha_k p_k^{(x)}$ with $p_k^{(x)} = -A^{-1} B p_k^{(y)}$





Saddle point problem and indefinite constraint preconditioner

$$\begin{pmatrix} A & B \\ B^T & 0 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} f \\ 0 \end{pmatrix}, \quad \mathcal{P} = \begin{pmatrix} I & B \\ B^T & 0 \end{pmatrix}$$

$$\mathcal{A}\mathcal{P}^{-1} = \begin{pmatrix} A(I-\Pi)+\Pi & (A-I)B(B^TB)^{-1} \\ 0 & I \end{pmatrix}$$

$\Pi = B(B^TB)^{-1}B^T$ - orth. projector onto $span(B)$

[Lukšan, Vlček, 1998], [Gould, Keller, Wathen 2000]
[Perugia, Simoncini, Arioli, 1999], [R, Simoncini, 2002]

Indefinite constraint preconditioner: spectral properties

$\mathcal{A}\mathcal{P}^{-1}$ **nonsymmetric** and **non-diagonalizable**!
but it has a 'nice' spectrum:

$$
\begin{aligned}
\sigma(\mathcal{A}\mathcal{P}^{-1}) &\subset \{1\} \cup \sigma(A(I-\Pi)+\Pi) \\
&\subset \{1\} \cup \sigma((I-\Pi)A(I-\Pi)) - \{0\}
\end{aligned}
$$

and only 2 by 2 Jordan blocks!

[Lukšan, Vlček 1998], [Gould, Wathen, Keller, 1999], [Perugia, Simoncini 1999]

Krylov method with the constraint preconditioner: basic properties

$$\begin{pmatrix} x_0 \\ y_0 \end{pmatrix}, r_0 = \begin{pmatrix} s_0 \\ 0 \end{pmatrix}, e_{k+1} = \begin{pmatrix} x - x_{k+1} \\ y - y_{k+1} \end{pmatrix}$$

$$r_{k+1} = \begin{pmatrix} f \\ 0 \end{pmatrix} - \begin{pmatrix} A & B \\ B^T & 0 \end{pmatrix} \begin{pmatrix} x_{k+1} \\ y_{k+1} \end{pmatrix}$$

$$r_0 = \begin{pmatrix} s_0 \\ 0 \end{pmatrix} \Rightarrow r_{k+1} = \begin{pmatrix} s_{k+1} \\ 0 \end{pmatrix}$$
$$\Rightarrow B^T(x - x_{k+1}) = 0$$
$$\Rightarrow x_{k+1} \in Null(B^T)!$$

Preconditioned CG method: error norm

$$r_{k+1}^T \mathcal{P}^{-1} r_j = 0, \; j = 0, \ldots, k$$

x_{k+1} is an iterate from CG applied to

$$(I - \Pi)A(I - \Pi)x = (I - \Pi)f!$$

satisfying

$$\|x - x_{k+1}\|_A = \min_{u \in x_0 + span\{(I-\Pi)s_j\}} \|x - u\|_A$$

[Lukšan, Vlček 1998], [Gould, Wathen, Keller, 1999]

Preconditioned CG algorithm

$$\begin{pmatrix} x_0 \\ y_0 \end{pmatrix},\ r_0 = b - \mathcal{A} \begin{pmatrix} x_0 \\ y_0 \end{pmatrix} = \begin{pmatrix} s_0 \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} p_0^{(x)} \\ p_0^{(y)} \end{pmatrix} = \mathcal{P}^{-1} r_0 = \mathcal{P}^{-1} \begin{pmatrix} s_0 \\ 0 \end{pmatrix}$$

$k = 0, 1, \dots$

$$\alpha_k = (\begin{pmatrix} s_k \\ 0 \end{pmatrix}, \mathcal{P}^{-1} \begin{pmatrix} s_k \\ 0 \end{pmatrix})/(\mathcal{A} \begin{pmatrix} p_k^{(x)} \\ p_k^{(y)} \end{pmatrix}, \begin{pmatrix} p_k^{(x)} \\ p_k^{(y)} \end{pmatrix}) \qquad \alpha_k = (r_k, z_k)/(\mathcal{A} p_k, p_k)$$

$$\begin{pmatrix} x_{k+1} \\ y_{k+1} \end{pmatrix} = \begin{pmatrix} x_k \\ y_k \end{pmatrix} + \alpha_k \begin{pmatrix} p_k^{(x)} \\ p_k^{(y)} \end{pmatrix}$$

$$r_{k+1} = r_k - \alpha_k \mathcal{A} \begin{pmatrix} p_k^{(x)} \\ p_k^{(y)} \end{pmatrix} = \begin{pmatrix} s_{k+1} \\ 0 \end{pmatrix} \qquad z_{k+1} = \mathcal{P}^{-1} r_{k+1}$$

$$\beta_k = (\begin{pmatrix} s_{k+1} \\ 0 \end{pmatrix}, \mathcal{P}^{-1} \begin{pmatrix} s_{k+1} \\ 0 \end{pmatrix})/(\begin{pmatrix} s_k \\ 0 \end{pmatrix}, \mathcal{P}^{-1} \begin{pmatrix} s_k \\ 0 \end{pmatrix}) \qquad \beta_k = (r_{k+1}, z_{k+1})/(r_k, z_k)$$

$$\begin{pmatrix} p_{k+1}^{(x)} \\ p_{k+1}^{(y)} \end{pmatrix} = \mathcal{P}^{-1} \begin{pmatrix} s_{k+1} \\ 0 \end{pmatrix} + \beta_k \begin{pmatrix} p_k^{(x)} \\ p_k^{(y)} \end{pmatrix} \qquad p_{k+1} = z_{k+1} + \beta_k p_k$$

Preconditioned CG method: residual norm

$$\|x_{k+1} - x\| \to 0$$

but in general

$$y_{k+1} \not\to y$$

which is reflected in

$$\|r_{k+1}\| = \left\| \begin{pmatrix} s_{k+1} \\ 0 \end{pmatrix} \right\| \not\to 0!$$

but under appropriate scaling yes!

Preconditioned CG method: residual norm

$$x_{k+1} \to x$$

$$x - x_{k+1} = \phi_{k+1}((I - \Pi)A(I - \Pi))(x - x_0)$$

$$s_{k+1} = \phi_{k+1}(A(I - \Pi) + \Pi)s_0$$

$$\sigma((I - \Pi)A(I - \Pi)) \sim \sigma(A(I - \Pi) + \Pi)?$$

$$\{1\} \in \sigma((I - \Pi)\alpha A(I - \Pi)) - \{0\}$$

$$\Rightarrow \|r_{k+1}\| = \left\| \begin{pmatrix} s_{k+1} \\ 0 \end{pmatrix} \right\| \to 0!$$

How to avoid misconvergence?

- Scaling by a constant $\alpha > 0$ such that

$$\{1\} \in conv(\sigma((I-\Pi)\alpha A(I-\Pi)) - \{0\})$$

$$\begin{pmatrix} A & B \\ B^T & 0 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} f \\ 0 \end{pmatrix} \quad \Longleftrightarrow \quad \begin{pmatrix} \alpha A & B \\ B^T & 0 \end{pmatrix} \begin{pmatrix} x \\ \alpha y \end{pmatrix} = \begin{pmatrix} \alpha f \\ 0 \end{pmatrix}$$

$$v: \quad \|(I-\Pi)v\| \neq 0, \quad \alpha = \frac{1}{((I-\Pi)v, A(I-\Pi)v)}!$$

- Scaling by a diagonal $A \rightarrow (diag(A))^{-1/2} A (diag(A))^{-1/2}$ often gives what we want!
- Different direction vector $p_k^{(y)}$ so that $\|r_{k+1}\| = \|s_{k+1}\|$ is locally minimized!

$$y_{k+1} = y_k + (B^T B)^{-1} B^T s_k$$

[Braess, Deuflhard,Lipikov 1999], [Hribar, Gould, Nocedal, 1999], [Jiránek, R, 2008]

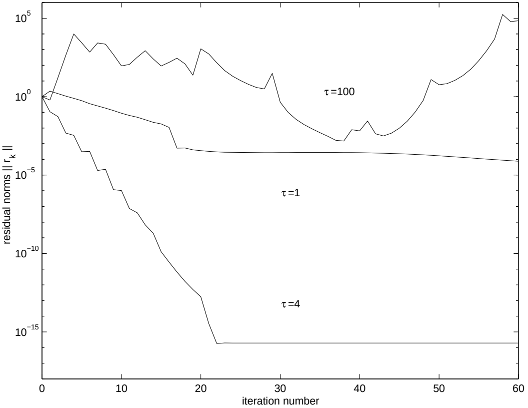
Numerical experiments: a small model example

$$A = \mathrm{tridiag}(1,4,1) \in \mathsf{R}^{25,25},\ B = \mathrm{rand}(25,5) \in \mathsf{R}^{25,5}$$
$$f = \mathrm{rand}(25,1) \in \mathsf{R}^{25}$$

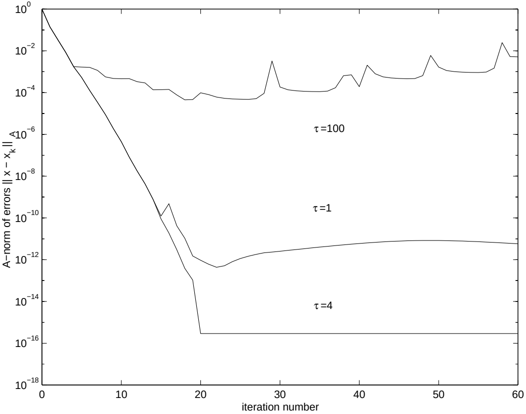
$$\sigma(A) \subset [2.0146, 5.9854]$$

$$\alpha = 1/\tau \quad \sigma(\begin{pmatrix} \alpha A & B \\ B^T & 0 \end{pmatrix} \begin{pmatrix} I & B \\ B^T & 0 \end{pmatrix}^{-1})$$

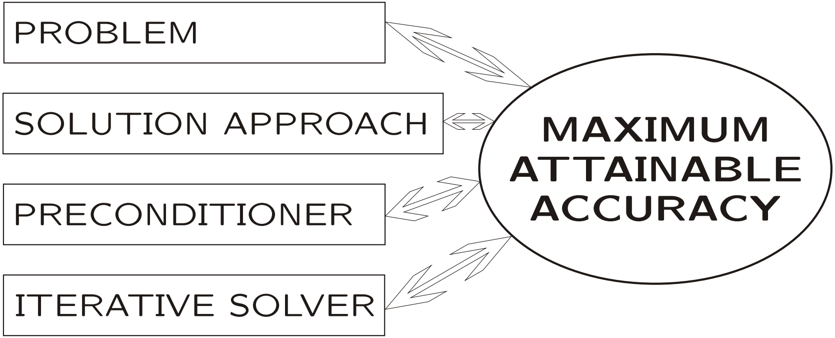
$1/100$	$[0.0207, 0.0586] \cup \{1\}$
$1/10$	$[0.2067, 0.5856] \cup \{1\}$
$\mathbf{1/4}$	$[\mathbf{0.5170}, \mathbf{1.4641}]$
1	$\{1\} \cup [2.0678, 5.8563]$
4	$\{1\} \cup [8.2712, 23.4252]$



10^{5}
10^{0}
10^{-5}
10^{-10}
10^{-15}
residual norms $\| r_k \|$
$\tau = 100$
$\tau = 1$
$\tau = 4$
0
10
20
30
40
50
60
iteration number

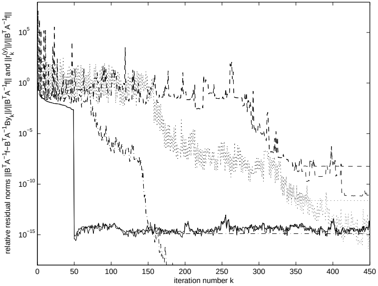


A−norm of errors || x − x_k ||_A
iteration number
τ =100
τ =1
τ =4


PROBLEM
SOLUTION APPROACH
PRECONDITIONER
ITERATIVE SOLVER
MAXIMUM
ATTAINABLE
ACCURACY

Conclusions: segregated solution approach

- The accuracy measured by the residuals of the saddle point problem depends on the choice of the back-substitution scheme [Jiránek, R, 2008]. The schemes with (generic or corrected substitution) updates deliver approximate solutions which satisfy either the first or second block equation to working accuracy.
- Care must be taken when solving nonsymmetric systems [Jiránek, R, 2008], all bounds of the limiting accuracy depend on the maximum norm of computed iterates, cf. [Greenbaum 1994,1997], [Sleijpen, et al. 1994].



Conclusions: coupled approach with indefinite preconditioner

- Short-term recurrence methods are applicable for saddle point problems with indefinite preconditioning at a cost comparable to that of symmetric solvers. There is a tight connection between the simplified Bi-CG algorithm and the classical CG.
- The convergence of CG applied to saddle point problem with indefinite preconditioner for all right-hand side vectors is not guaranteed. For a particular set of right-hand sides the convergence can be achieved by the appropriate scaling of the saddle point problem.
- Since the maximum attainable accuracy depends heavily on the size of computed residuals, a good scaling of the problems leads to approximate solutions satisfying both two block equations to the working accuracy.

Thank you for your attention.

http://www.cs.cas.cz/∼miro

M. Rozložník and V. Simoncini, Krylov subspace methods for saddle point problems with indefinite preconditioning, *SIAM J. Matrix Anal. Appl., 24 (2002), pp. 368–391.*

P. Jiránek and M. Rozložník. Limiting accuracy of segregated solution methods for nonsymmetric saddle point problems. *J. Comput. Appl. Math.* 215 (2008), pp. 28-37.

P. Jiránek and M. Rozložník. Maximum attainable accuracy of inexact saddle point solvers. *SIAM J. Matrix Anal. Appl.*, 29(4):1297–1321, 2008.