

Projected Schur Complement Method for Solving Non-Symmetric Saddle-Point Systems (Arising from Fictitious Domain Approaches)

Jaroslav Haslinger, Charles University, Prague

Tomáš Kozubek, VŠB–TU Ostrava

Radek Kučera, VŠB–TU Ostrava

PRAHA, April 2007

OUTLINE

Preliminaries on saddle-point systems

Projected Schur complement method

Projected BiCGSTAB algorithm

Hierarchical multigrid

Poisson-like solver for singular matrices

Numerical experiments

OUTLINE

Preliminaries on saddle-point systems

Projected Schur complement method

Projected BiCGSTAB algorithm

Hierarchical multigrid

Poisson-like solver for singular matrices

Numerical experiments

Formulation: Non-symmetric saddle-point system

$$\begin{pmatrix} \mathbf{A} & \mathbf{B}_1^\top \\ \mathbf{B}_2 & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{u} \\ \lambda \end{pmatrix} = \begin{pmatrix} \mathbf{f} \\ \mathbf{g} \end{pmatrix}$$

Assumptions

\mathbf{A} ... non-symmetric $(n \times n)$ -matrix
... singular with $p = \dim \text{Ker } \mathbf{A}$ as $V_h \approx H_{per}^1(\Omega)$
... actions of A^\dagger are "cheap"

$\mathbf{B}_1, \mathbf{B}_2$... full rank $(m \times n)$ -matrices, $m \ll n$
... sparse, their actions are cheap
... $\mathbf{B}_1 \neq \mathbf{B}_2$

Algorithms based on Schur complement reduction

- Case 1: symmetric, non-singular
- Case 2: non-symmetric, non-singular
- Case 3: symmetric, singular
- Case 4: non-symmetric, singular

Case 1: symmetric, non-singular

$$\begin{pmatrix} \mathbf{A} & \mathbf{B}^\top \\ \mathbf{B} & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{u} \\ \boldsymbol{\lambda} \end{pmatrix} = \begin{pmatrix} \mathbf{f} \\ \mathbf{g} \end{pmatrix} \implies \mathbf{u} = \mathbf{A}^{-1}(\mathbf{f} - \mathbf{B}^\top \boldsymbol{\lambda})$$
$$\implies \underbrace{\mathbf{B}\mathbf{A}^{-1}\mathbf{B}^\top}_{\text{negative Schur complement } \mathbf{S}} \boldsymbol{\lambda} = \mathbf{B}\mathbf{A}^{-1}\mathbf{f} - \mathbf{g}$$

Algorithm

- 1° Assemble $\mathbf{d} := \mathbf{B}\mathbf{A}^{-1}\mathbf{f} - \mathbf{g}$.
- 2° Iteratively solve $\mathbf{S}\boldsymbol{\lambda} = \mathbf{d}$ with $\mathbf{S} := \mathbf{B}\mathbf{A}^{-1}\mathbf{B}^\top$.
- 3° Assemble $\mathbf{u} := \mathbf{A}^{-1}(\mathbf{f} - \mathbf{B}^\top \boldsymbol{\lambda})$.

Matrix-vector products $\mathbf{S}\boldsymbol{\mu}$ are performed by:

$$\mathbf{S}\boldsymbol{\mu} := (\mathbf{B} (\mathbf{A}^{-1} (\mathbf{B}^\top \boldsymbol{\mu})))$$

Case 2: non-symmetric, non-singular

$$\begin{aligned} \begin{pmatrix} \mathbf{A} & \mathbf{B}_1^\top \\ \mathbf{B}_2 & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{u} \\ \boldsymbol{\lambda} \end{pmatrix} &= \begin{pmatrix} \mathbf{f} \\ \mathbf{g} \end{pmatrix} \implies \mathbf{u} = \mathbf{A}^{-1}(\mathbf{f} - \mathbf{B}_1^\top \boldsymbol{\lambda}) \\ &\implies \underbrace{\mathbf{B}_2 \mathbf{A}^{-1} \mathbf{B}_1^\top}_{\text{negative Schur complement } \mathbf{S}} \boldsymbol{\lambda} = \mathbf{B}_2 \mathbf{A}^{-1} \mathbf{f} - \mathbf{g} \end{aligned}$$

Algorithm is analogous.

- an iterative method for non-symmetric matrices is required (GMRES, BiCG, BiCGSTAB, ...)

$$\mathcal{A} := \begin{pmatrix} \mathbf{A} & \mathbf{B}_1^\top \\ \mathbf{B}_2 & \mathbf{0} \end{pmatrix} = \begin{pmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{B}_2 \mathbf{A}^{-1} & \mathbf{I} \end{pmatrix} \begin{pmatrix} \mathbf{A} & \mathbf{B}_1^\top \\ \mathbf{0} & -\mathbf{S} \end{pmatrix}$$

Theorem. Let \mathbf{A} be non-singular. Then \mathcal{A} is invertible **iff** \mathbf{S} is invertible.

Case 3: symmetric, singular (positive semidefinite \mathbf{A} , FETI)

- a generalized inverse \mathbf{A}^\dagger satisfying $\mathbf{A} = \mathbf{A}\mathbf{A}^\dagger\mathbf{A}$
- an $(n \times p)$ -matrix \mathbf{N} whose columns span $\text{Ker } \mathbf{A}$

$$\mathbf{A}\mathbf{u} + \mathbf{B}^\top \boldsymbol{\lambda} = \mathbf{f} \quad \Longleftrightarrow \quad \mathbf{f} - \mathbf{B}^\top \boldsymbol{\lambda} \in \text{Im } \mathbf{A} \perp \text{Ker } \mathbf{A}$$

$$\Downarrow$$

$$\mathbf{u} = \mathbf{A}^\dagger(\mathbf{f} - \mathbf{B}^\top \boldsymbol{\lambda}) + \mathbf{N}\boldsymbol{\alpha}$$

$$\Downarrow$$

$$\mathbf{N}^\top(\mathbf{f} - \mathbf{B}^\top \boldsymbol{\lambda}) = \mathbf{0}$$

&

The reduced system:

$$\mathbf{B}\mathbf{u} = \mathbf{g}$$

$$\begin{pmatrix} \mathbf{B}\mathbf{A}^\dagger\mathbf{B}^\top & -\mathbf{B}\mathbf{N} \\ -\mathbf{N}^\top\mathbf{B}^\top & \mathbf{0} \end{pmatrix} \begin{pmatrix} \boldsymbol{\lambda} \\ \boldsymbol{\alpha} \end{pmatrix} = \begin{pmatrix} \mathbf{B}\mathbf{A}^\dagger\mathbf{f} - \mathbf{g} \\ -\mathbf{N}^\top\mathbf{f} \end{pmatrix}$$

$$\Downarrow$$

$$\mathbf{B}\mathbf{A}^\dagger\mathbf{B}^\top \boldsymbol{\lambda} - \mathbf{B}\mathbf{N}\boldsymbol{\alpha} = \mathbf{B}\mathbf{A}^\dagger\mathbf{f} - \mathbf{g}$$

Case 4: non-symmetric, singular

- a generalized inverse \mathbf{A}^\dagger
- columns of $(n \times p)$ -matrices \mathbf{N} , \mathbf{M} span $\text{Ker } \mathbf{A}$, $\text{Ker } \mathbf{A}^\top$, respectively

$$\mathbf{A}\mathbf{u} + \mathbf{B}_1^\top \boldsymbol{\lambda} = \mathbf{f} \quad \Longleftrightarrow \quad \mathbf{f} - \mathbf{B}_1^\top \boldsymbol{\lambda} \in \text{Im } \mathbf{A} \perp \text{Ker } \mathbf{A}^\top$$

$$\Downarrow$$

$$\mathbf{u} = \mathbf{A}^\dagger(\mathbf{f} - \mathbf{B}_1^\top \boldsymbol{\lambda}) + \mathbf{N}\boldsymbol{\alpha}$$

$$\Downarrow$$

$$\mathbf{M}^\top(\mathbf{f} - \mathbf{B}_1^\top \boldsymbol{\lambda}) = \mathbf{0}$$

&

The reduced system:

$$\mathbf{B}_2\mathbf{u} = \mathbf{g}$$

$$\begin{pmatrix} \mathbf{B}_2\mathbf{A}^\dagger\mathbf{B}_1^\top & -\mathbf{B}_2\mathbf{N} \\ -\mathbf{M}^\top\mathbf{B}_1^\top & \mathbf{0} \end{pmatrix} \begin{pmatrix} \boldsymbol{\lambda} \\ \boldsymbol{\alpha} \end{pmatrix} = \begin{pmatrix} \mathbf{B}_2\mathbf{A}^\dagger\mathbf{f} - \mathbf{g} \\ -\mathbf{M}^\top\mathbf{f} \end{pmatrix}$$

$$\Downarrow$$

$$\mathbf{B}_2\mathbf{A}^\dagger\mathbf{B}_1^\top \boldsymbol{\lambda} - \mathbf{B}_2\mathbf{N}\boldsymbol{\alpha} = \mathbf{B}_2\mathbf{A}^\dagger\mathbf{f} - \mathbf{g}$$

Theorem The saddle-point matrix $\mathcal{A} := \begin{pmatrix} \mathbf{A} & \mathbf{B}_1^\top \\ \mathbf{B}_2 & \mathbf{0} \end{pmatrix}$ is invertible **iff**

$$\left. \begin{array}{l} \mathbf{B}_1 \text{ has full row-rank} \\ \text{Ker } \mathbf{A} \cap \text{Ker } \mathbf{B}_2 = \{\mathbf{0}\} \\ \mathbf{A} \text{ Ker } \mathbf{B}_2 \cap \text{Im } \mathbf{B}_1^\top = \{\mathbf{0}\} \end{array} \right\} \quad (\text{NSC})$$

The generalized Schur complement:

$$\mathcal{S} := \begin{pmatrix} -\mathbf{B}_2 \mathbf{A}^\dagger \mathbf{B}_1^\top & \mathbf{B}_2 \mathbf{N} \\ \mathbf{M}^\top \mathbf{B}_1^\top & \mathbf{0} \end{pmatrix}$$

Theorem 2. The following three statements are equivalent:

- The necessary and sufficient condition (NSC) holds.
- \mathcal{A} is invertible.
- \mathcal{S} is invertible.

OUTLINE

Preliminaries on saddle-point systems

Projected Schur complement method

Projected BiCGSTAB algorithm

Hierarchical multigrid

Poisson-like solver for singular matrices

Numerical experiments

Schur complement reduction:

$$\begin{pmatrix} \mathbf{A} & \mathbf{B}_1^\top \\ \mathbf{B}_2 & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{u} \\ \boldsymbol{\lambda} \end{pmatrix} = \begin{pmatrix} \mathbf{f} \\ \mathbf{g} \end{pmatrix} \iff \begin{cases} \begin{pmatrix} \mathbf{F} & \mathbf{G}_1^\top \\ \mathbf{G}_2 & \mathbf{0} \end{pmatrix} \begin{pmatrix} \boldsymbol{\lambda} \\ \alpha \end{pmatrix} = \begin{pmatrix} \mathbf{d} \\ \mathbf{e} \end{pmatrix} \\ \mathbf{u} = \mathbf{A}^\dagger(\mathbf{f} - \mathbf{B}_1^\top \boldsymbol{\lambda}) + \mathbf{N}\alpha \end{cases}$$

How to solve the **reduced** system again with saddle-point structure?

- matrix-vector products via $\mathbf{F}\boldsymbol{\mu} := (\mathbf{B}_2 (\mathbf{A}^\dagger (\mathbf{B}_1^\top \boldsymbol{\mu})))$
- $\mathbf{G}_1, \mathbf{G}_2, \mathbf{d}, \mathbf{e}$ may be assembled

$$\left\{ \begin{array}{l} 1) \text{ Schur complement reduction again (the second elimination)} \\ \quad \mathbf{E}\boldsymbol{\alpha} = \mathbf{r} \text{ with } \mathbf{E} := \mathbf{G}_2\mathbf{F}^{-1}\mathbf{G}_1^\top \text{ then } \boldsymbol{\lambda} := \mathbf{F}^{-1}(\mathbf{d} - \mathbf{G}_1^\top\boldsymbol{\alpha}) \text{ and } \mathbf{u} \\ \hspace{10em} (\text{R.K., Appl. Math. 50(2005)}) \\ 2) \text{ Null-space method} \\ \hspace{10em} (\text{Farhat, Mandel, Roux: FETI DDM, 1994}) \end{array} \right.$$

Null-space method:

$$\begin{pmatrix} \mathbf{F} & \mathbf{G}_1^\top \\ \mathbf{G}_2 & \mathbf{0} \end{pmatrix} \begin{pmatrix} \boldsymbol{\lambda} \\ \boldsymbol{\alpha} \end{pmatrix} = \begin{pmatrix} \mathbf{d} \\ \mathbf{e} \end{pmatrix}$$

Two orthogonal projectors \mathbf{P}_1 and \mathbf{P}_2 onto $\text{Ker } \mathbf{G}_1$ and $\text{Ker } \mathbf{G}_2$:

$$\mathbf{P}_k : \mathbb{R}^m \mapsto \text{Ker } \mathbf{G}_k, \quad \mathbf{P}_k := \mathbf{I} - \mathbf{G}_k^\top (\mathbf{G}_k \mathbf{G}_k^\top)^{-1} \mathbf{G}_k, \quad k = 1, 2$$

Property: $\mathbf{P}_k \mathbf{G}_k^\top = \mathbf{0} \iff \text{Ker } \mathbf{P}_k = \text{Im } \mathbf{G}_k^\top$

• \mathbf{P}_1 splits the saddle-point structure: $\mathbf{P}_1 \mathbf{F} \boldsymbol{\lambda} + \mathbf{P}_1 \mathbf{G}_1^\top \boldsymbol{\alpha} = \mathbf{P}_1 \mathbf{d}$

$$\mathbf{P}_1 \mathbf{F} \boldsymbol{\lambda} = \mathbf{P}_1 \mathbf{d}, \quad \mathbf{G}_2 \boldsymbol{\lambda} = \mathbf{e}, \quad \boldsymbol{\alpha} := (\mathbf{G}_1 \mathbf{G}_1^\top)^{-1} (\mathbf{G}_1 \mathbf{d} - \mathbf{G}_1 \mathbf{F} \boldsymbol{\lambda})$$

• \mathbf{P}_2 decomposes $\boldsymbol{\lambda} = \boldsymbol{\lambda}_{\text{Im}} + \boldsymbol{\lambda}_{\text{Ker}}$, $\boldsymbol{\lambda}_{\text{Im}} \in \text{Im } \mathbf{G}_2^\top$, $\boldsymbol{\lambda}_{\text{Ker}} \in \text{Ker } \mathbf{G}_2$

At first: $\mathbf{G}_2 \boldsymbol{\lambda} = \mathbf{G}_2 \boldsymbol{\lambda}_{\text{Im}} = \mathbf{e} \implies \boldsymbol{\lambda}_{\text{Im}} := \mathbf{G}_2^\top (\mathbf{G}_2 \mathbf{G}_2^\top)^{-1} \mathbf{e}$

At second: $\mathbf{P}_1 \mathbf{F} \boldsymbol{\lambda}_{\text{Ker}} = \mathbf{P}_1 (\mathbf{d} - \mathbf{F} \boldsymbol{\lambda}_{\text{Im}})$ on $\text{Ker } \mathbf{G}_2$

Formally:

$$\mathbf{P}_1 \mathbf{F} \mathbf{P}_2 \boldsymbol{\lambda}_{\text{Ker}} = \mathbf{P}_1 (\mathbf{d} - \mathbf{F} \boldsymbol{\lambda}_{\text{Im}})$$

Theorem The linear operator $\mathbf{P}_1\mathbf{F}: Ker \mathbf{G}_2 \mapsto Ker \mathbf{G}_1$ is invertible.

Proof.

As both null-spaces $Ker \mathbf{G}_1$ and $Ker \mathbf{G}_2$ have the same dimension $m - p$, it is enough to prove that $\mathbf{P}_1\mathbf{F}$ is injective.

Let $\boldsymbol{\mu} \in Ker \mathbf{G}_2$ be such that $\mathbf{P}_1\mathbf{F}\boldsymbol{\mu} = \mathbf{0}$. Then $\mathbf{F}\boldsymbol{\mu} \in Ker \mathbf{P}_1 = Im \mathbf{G}_1^\top$ and, therefore, there is $\boldsymbol{\beta} \in \mathbb{R}^p$ so that

$$\mathbf{F}\boldsymbol{\mu} = \mathbf{G}_1^\top \boldsymbol{\beta} \quad \text{and} \quad \mathbf{G}_2\boldsymbol{\mu} = \mathbf{0}.$$

We obtain

$$\begin{pmatrix} \mathbf{F} & \mathbf{G}_1^\top \\ \mathbf{G}_2 & \mathbf{0} \end{pmatrix} \begin{pmatrix} \boldsymbol{\mu} \\ -\boldsymbol{\beta} \end{pmatrix} = \begin{pmatrix} \mathbf{0} \\ \mathbf{0} \end{pmatrix},$$

where the matrix is the (negative) Schur complement \mathcal{S} that is invertible and therefore $\boldsymbol{\mu} = \mathbf{0}$.

Algorithm PSCM

Step 1.a: Assemble $\mathbf{G}_1 := -\mathbf{N}^\top \mathbf{B}_2^\top$, $\mathbf{G}_2 := -\mathbf{M}^\top \mathbf{B}_1^\top$.

Step 1.b: Assemble $\mathbf{d} := \mathbf{B}_2 \mathbf{A}^\dagger \mathbf{f} - \mathbf{g}$, $\mathbf{e} := -\mathbf{M}^\top \mathbf{f}$.

Step 1.c: Assemble $\mathbf{H}_1 := (\mathbf{G}_1 \mathbf{G}_1^\top)^{-1}$, $\mathbf{H}_2 := (\mathbf{G}_2 \mathbf{G}_2^\top)^{-1}$.

Step 1.d: Assemble $\boldsymbol{\lambda}_{Im} := \mathbf{G}_2^\top \mathbf{H}_2 \mathbf{e}$, $\tilde{\mathbf{d}} := \mathbf{P}_1(\mathbf{d} - \mathbf{F} \boldsymbol{\lambda}_{Im})$.

Step 1.e: Solve $\mathbf{P}_1 \mathbf{F} \boldsymbol{\lambda}_{Ker} = \tilde{\mathbf{d}}$ on $Ker \mathbf{G}_2$.

Step 1.f: Assemble $\boldsymbol{\lambda} := \boldsymbol{\lambda}_{Im} + \boldsymbol{\lambda}_{Ker}$.

Step 2: Assemble $\boldsymbol{\alpha} := \mathbf{H}_1 \mathbf{G}_1(\mathbf{d} - \mathbf{F} \boldsymbol{\lambda})$.

Step 3: Assemble $\mathbf{u} := \mathbf{A}^\dagger(\mathbf{f} - \mathbf{B}_1^\top \boldsymbol{\lambda}) + \mathbf{N} \boldsymbol{\alpha}$.

- an iterative **projected** Krylov subspace method for non-symmetric operators can be used in Step 1.e
- matrix-vector products $\mathbf{P}_k \boldsymbol{\mu}$, $k = 1, 2$ are computed by:

$$\mathbf{P}_k \boldsymbol{\mu} := \boldsymbol{\mu} - (\mathbf{G}_k^\top (\mathbf{H}_k (\mathbf{G}_k \boldsymbol{\mu})))$$

OUTLINE

Preliminaries on saddle-point systems

Projected Schur complement method

Projected BiCGSTAB algorithm

Hierarchical multigrid

Poisson-like solver for singular matrices

Numerical experiments

Find $\boldsymbol{\lambda} \in \mathbb{R}^m$ so that $\mathbf{F}\boldsymbol{\lambda} = \mathbf{d}$, where $\mathbf{d} \in \mathbb{R}^m$.

Algorithm BiCGSTAB $[\epsilon, \boldsymbol{\lambda}^0, \mathbf{F}, \mathbf{d}] \rightarrow \boldsymbol{\lambda}$

Initialize: $\mathbf{r}^0 := \mathbf{d} - \mathbf{F}\boldsymbol{\lambda}^0$, $\mathbf{p}^0 := \mathbf{r}^0$, $\tilde{\mathbf{r}}^0$ arbitrary, $k := 0$

While $\|\mathbf{r}^k\| > \epsilon$

1° $\tilde{\mathbf{p}}^k := \mathbf{F}\mathbf{p}^k$

2° $\alpha_k := (\mathbf{r}^k)^\top \tilde{\mathbf{r}}^0 / (\tilde{\mathbf{p}}^k)^\top \tilde{\mathbf{r}}^0$

3° $\mathbf{s}^k := \mathbf{r}^k - \alpha_k \tilde{\mathbf{p}}^k$

4° $\tilde{\mathbf{s}}^k := \mathbf{F}\mathbf{s}^k$

5° $\omega_k := (\tilde{\mathbf{s}}^k)^\top \mathbf{s}^k / (\tilde{\mathbf{s}}^k)^\top \tilde{\mathbf{s}}^k$

6° $\boldsymbol{\lambda}^{k+1} := \boldsymbol{\lambda}^k + \alpha_k \mathbf{p}^k + \omega_k \mathbf{s}^k$

7° $\mathbf{r}^{k+1} := \mathbf{s}^k - \omega_k \tilde{\mathbf{s}}^k$

8° $\beta_{k+1} := (\alpha_k / \omega_k) (\mathbf{r}^{k+1})^\top \tilde{\mathbf{r}}^0 / (\mathbf{r}^k)^\top \tilde{\mathbf{r}}^0$

9° $\mathbf{p}^{k+1} := \mathbf{r}^{k+1} + \beta_{k+1} (\mathbf{p}^k - \omega_k \tilde{\mathbf{p}}^k)$

10° $k := k + 1$

end

(Van der Vorst, 1992)

Find $\lambda \in \text{Ker } \mathbf{G}_2$ so that $\mathbf{P}_1 \mathbf{F} \lambda = \tilde{\mathbf{d}}$, where $\tilde{\mathbf{d}} \in \text{Ker } \mathbf{G}_1$.

Algorithm ProjBiCGSTAB $[\epsilon, \lambda^0, \mathbf{F}, \mathbf{P}_1, \mathbf{P}_2, \tilde{\mathbf{d}}] \rightarrow \lambda$

Initialize: $\lambda^0 \in \text{Ker } \mathbf{G}_2$, $\mathbf{r}^0 := \tilde{\mathbf{d}} - \mathbf{P}_1 \mathbf{F} \lambda^0$, $\mathbf{p}^0 := \mathbf{r}^0$, $\tilde{\mathbf{r}}^0$ arbitrary, $k := 0$

While $\|\mathbf{r}^k\| > \epsilon$

$$1^\circ \quad \tilde{\mathbf{p}}^k := \mathbf{P}_1 \mathbf{F} \mathbf{p}^k$$

$$2^\circ \quad \alpha_k := (\mathbf{r}^k)^\top \tilde{\mathbf{r}}^0 / (\tilde{\mathbf{p}}^k)^\top \tilde{\mathbf{r}}^0$$

$$3^\circ \quad \mathbf{s}^k := \mathbf{r}^k - \alpha_k \tilde{\mathbf{p}}^k$$

$$4^\circ \quad \tilde{\mathbf{s}}^k := \mathbf{P}_1 \mathbf{F} \mathbf{s}^k$$

$$5^\circ \quad \omega_k := (\tilde{\mathbf{s}}^k)^\top \mathbf{s}^k / (\tilde{\mathbf{s}}^k)^\top \tilde{\mathbf{s}}^k$$

$$6^\circ \quad \lambda^{k+1} := \lambda^k + \alpha_k \mathbf{P}_2 \mathbf{p}^k + \omega_k \mathbf{P}_2 \mathbf{s}^k$$

$$7^\circ \quad \mathbf{r}^{k+1} := \mathbf{s}^k - \omega_k \tilde{\mathbf{s}}^k$$

$$8^\circ \quad \beta_{k+1} := (\alpha_k / \omega_k) (\mathbf{r}^{k+1})^\top \tilde{\mathbf{r}}^0 / (\mathbf{r}^k)^\top \tilde{\mathbf{r}}^0$$

$$9^\circ \quad \mathbf{p}^{k+1} := \mathbf{r}^{k+1} + \beta_{k+1} (\mathbf{p}^k - \omega_k \tilde{\mathbf{p}}^k)$$

$$10^\circ \quad k := k + 1$$

end

Formally solve $\mathbf{P}_2\mathbf{P}_1\mathbf{F}\boldsymbol{\lambda} = \mathbf{P}_2\tilde{\mathbf{d}}$, with $\boldsymbol{\lambda}^0 \in \text{Ker } \mathbf{G}_2$.

Algorithm ProjBiCGSTAB $[\epsilon, \boldsymbol{\lambda}^0, \mathbf{F}, \mathbf{P}_1, \mathbf{P}_2, \tilde{\mathbf{d}}] \rightarrow \boldsymbol{\lambda}$

Initialize: $\boldsymbol{\lambda}^0 \in \text{Ker } \mathbf{G}_2$, $\mathbf{r}^0 := \mathbf{P}_2(\tilde{\mathbf{d}} - \mathbf{P}_1\mathbf{F}\boldsymbol{\lambda}^0)$, $\mathbf{p}^0 := \mathbf{r}^0$, $\tilde{\mathbf{r}}^0$, $k := 0$

While $\|\mathbf{r}^k\| > \epsilon$

$$1^\circ \quad \tilde{\mathbf{p}}^k := \mathbf{P}_2\mathbf{P}_1\mathbf{F}\mathbf{p}^k$$

$$2^\circ \quad \alpha_k := (\mathbf{r}^k)^\top \tilde{\mathbf{r}}^0 / (\tilde{\mathbf{p}}^k)^\top \tilde{\mathbf{r}}^0$$

$$3^\circ \quad \mathbf{s}^k := \mathbf{r}^k - \alpha_k \tilde{\mathbf{p}}^k$$

$$4^\circ \quad \tilde{\mathbf{s}}^k := \mathbf{P}_2\mathbf{P}_1\mathbf{F}\mathbf{s}^k$$

$$5^\circ \quad \omega_k := (\tilde{\mathbf{s}}^k)^\top \mathbf{s}^k / (\tilde{\mathbf{s}}^k)^\top \tilde{\mathbf{s}}^k$$

$$6^\circ \quad \boldsymbol{\lambda}^{k+1} := \boldsymbol{\lambda}^k + \alpha_k \mathbf{p}^k + \omega_k \mathbf{s}^k$$

$$7^\circ \quad \mathbf{r}^{k+1} := \mathbf{s}^k - \omega_k \tilde{\mathbf{s}}^k$$

$$8^\circ \quad \beta_{k+1} := (\alpha_k / \omega_k) (\mathbf{r}^{k+1})^\top \tilde{\mathbf{r}}^0 / (\mathbf{r}^k)^\top \tilde{\mathbf{r}}^0$$

$$9^\circ \quad \mathbf{p}^{k+1} := \mathbf{r}^{k+1} + \beta_{k+1} (\mathbf{p}^k - \omega_k \tilde{\mathbf{p}}^k)$$

$$10^\circ \quad k := k + 1$$

end

OUTLINE

Preliminaries on saddle-point systems

Projected Schur complement method

Projected BiCGSTAB algorithm

Hierarchical multigrid

Poisson-like solver for singular matrices

Numerical experiments

Consider a family of nested partitions of the fictitious domain Ω with stepsizes:

$$h_j, \quad 0 \leq j \leq J$$

- the first iterate is determined by the result from the nearest lower level
- the terminating tolerance ϵ on each level is $\epsilon := \nu h_j^p$

Algorithm: Hierarchical Multigrid Scheme

Initialize: Let $\lambda_{Ker}^{0,(0)} \in Ker(\mathbf{G}_2^{(0)})$ be given.

ProjBiCGSTAB $[\nu h_0^p, \lambda_{Ker}^{0,(0)}, \mathbf{F}^{(0)}, \mathbf{P}_1^{(0)}, \mathbf{P}_2^{(0)}, \tilde{\mathbf{d}}^{(0)}] \rightarrow \lambda_{Ker}(0).$

For $j = 1, \dots, J,$

1° prolongate $\lambda_{Ker}^{(j-1)} \rightarrow \tilde{\lambda}_{Ker}^{0,(j)}$

2° project $\tilde{\lambda}_{Ker}^{0,(j)} \rightarrow \lambda_{Ker}^{0,(j)} := \mathbf{P}_2^{(j)} \tilde{\lambda}_{Ker}^{0,(j)}$

3° ProjBiCGSTAB $[\nu h_j^p, \lambda_{Ker}^{0,(j)}, \mathbf{F}^{(j)}, \mathbf{P}_1^{(j)}, \mathbf{P}_2^{(j)}, \tilde{\mathbf{d}}^{(j)}] \rightarrow \lambda_{Ker}^{(j)}$

end

Return: $\lambda_{Ker} := \lambda_{Ker}^{(J)}.$

Motivation

\mathbf{u}^* ... exact solution of PDE problem

\mathbf{u} ... FEM approximation with respect to h with the convergence rate p

$$\|\mathbf{u}^* - \mathbf{u}\| \leq Ch^p, \quad \mathbf{A}\mathbf{u} = \mathbf{f}$$

\mathbf{u}^k ... the k -th iteration

$$\mathbf{u}^k \longrightarrow \mathbf{u}, \quad \mathbf{A}\mathbf{u}^k = \mathbf{f} + \mathbf{r}^k$$

When should be iterations terminated? $\|\mathbf{r}^k\| \leq \epsilon$, $\epsilon = ???$

$$\begin{aligned} \|\mathbf{u}^* - \mathbf{u}^k\| &\leq \|\mathbf{u}^* - \mathbf{u}\| + \|\mathbf{u} - \mathbf{u}^k\| \\ &\leq Ch^p + \|\mathbf{A}^{-1}\mathbf{r}^k\| \\ &\leq Ch^p + \|\mathbf{A}^{-1}\| \cdot \epsilon \\ &\leq (C + \|\mathbf{A}^{-1}\|\nu)h^p \quad \text{if } \epsilon := \nu h^p \end{aligned}$$

Control parameter ν may be choosen experimentally; $\nu \approx KC/\|\mathbf{A}^{-1}\|$.

OUTLINE

Preliminaries on saddle-point systems

Projected Schur complement method

Projected BiCGSTAB algorithm

Hierarchical multigrid

Poisson-like solver for singular matrices

Numerical experiments

Circulant matrices and Fourier transform

$$\mathbf{A} = \begin{pmatrix} a_1 & a_n & \dots & a_2 \\ a_2 & a_1 & \dots & a_3 \\ a_3 & a_2 & \dots & a_4 \\ \vdots & \vdots & \ddots & \vdots \\ a_n & a_{n-1} & \dots & a_1 \end{pmatrix} = (\mathbf{a}, \mathbf{T}\mathbf{a}, \mathbf{T}^2\mathbf{a}, \dots, \mathbf{T}^{n-1}\mathbf{a})$$

$$\widehat{\mathcal{T}_k f}(\omega) = \int_R f(x - k) e^{-ix\omega} dx = e^{-ik\omega} \widehat{f}(\omega)$$

$$\mathbf{X}\mathbf{A} = (\mathbf{D}\mathbf{x}_0, \mathbf{D}\mathbf{x}_1, \mathbf{D}\mathbf{x}_2, \dots, \mathbf{D}\mathbf{x}_{n-1}) = \mathbf{D}\mathbf{X}$$

Lamma: Let \mathbf{A} be circulant. Then

$$\mathbf{A} = \mathbf{X}^{-1}\mathbf{D}\mathbf{X},$$

where \mathbf{X} is the DFT matrix and $\mathbf{D} = \text{diag}(\widehat{\mathbf{a}})$, $\widehat{\mathbf{a}} = \mathbf{X}\mathbf{a}$, $\mathbf{a} = \mathbf{A}(:, 1)$.

Multiplying procedure: $\mathbf{A}^\dagger \mathbf{v} := \mathbf{X}^{-1} (\mathbf{D}^\dagger (\mathbf{X} \mathbf{v})) \quad \dots \quad \text{Moore-Penrose}$

$$\left. \begin{array}{ll} 0^\circ & \mathbf{d} := \text{fft}(\mathbf{a}) \\ 1^\circ & \mathbf{v} := \text{fft}(\mathbf{v}) \\ 2^\circ & \mathbf{v} := \mathbf{v} * \mathbf{d}^{-1} \\ 3^\circ & \mathbf{A}^\dagger \mathbf{v} := \text{ifft}(\mathbf{v}) \end{array} \right\} \mathcal{O}(2n \log_2 n)$$

Multiplying procedures: $\mathbf{N}\boldsymbol{\alpha}$, $\mathbf{N}^\top \mathbf{v}$ (and $\mathbf{M}\boldsymbol{\alpha}$, $\mathbf{M}^\top \mathbf{v}$)

As $\mathbf{A}\mathbf{N} = \mathbf{0}$, the matrix \mathbf{N} may be formed by eigenvectors corresponding to zero eigenvalues.

$$\mathbf{I} - \mathbf{D}\mathbf{D}^\dagger = \text{diag}(1, 1, 1, 0, \dots, 0) \implies \mathbf{X}^{-1} = (\mathbf{N}, \mathbf{Y}), \quad \mathbf{X}^{-1} = \begin{pmatrix} \mathbf{N}^\top \\ \mathbf{Y} \end{pmatrix}$$

Therefore we can define the operation: $\text{ind}(\boldsymbol{\alpha}) = \begin{pmatrix} \boldsymbol{\alpha} \\ \mathbf{0} \end{pmatrix} \in \mathbb{R}^n$

$$\left. \begin{array}{ll} 1^\circ & \mathbf{v}_\alpha := \text{ind}(\boldsymbol{\alpha}) \\ 2^\circ & \mathbf{N}\boldsymbol{\alpha} := \text{ifft}(\mathbf{v}_\alpha) \end{array} \quad \begin{array}{ll} 1^\circ & \mathbf{v} := \text{ifft}(\mathbf{v}) \\ 2^\circ & \mathbf{N}^\top \mathbf{v} := \text{ind}^{-1}(\mathbf{v}) \end{array} \right\} \mathcal{O}(n \log_2 n)$$

Kronecker product of matrices: $\mathbf{A}_x \in \mathbb{R}^{n_x \times n_x}, \mathbf{A}_y \in \mathbb{R}^{n_y \times n_y}$

$$\mathbf{A}_x \otimes \mathbf{A}_y = \begin{pmatrix} a_{11}^y \mathbf{A}_x & \dots & a_{1n_y}^y \mathbf{A}_x \\ \vdots & \ddots & \vdots \\ a_{n_y 1}^y \mathbf{A}_x & \dots & a_{n_y n_y}^y \mathbf{A}_x \end{pmatrix}$$

Lemma 1: $(\mathbf{A}_x \otimes \mathbf{A}_y)(\mathbf{B}_x \otimes \mathbf{B}_y) = \mathbf{A}_x \mathbf{B}_x \otimes \mathbf{A}_y \mathbf{B}_y$

$$(\mathbf{A}_x \otimes \mathbf{A}_y)^\dagger = \mathbf{A}_x^\dagger \otimes \mathbf{A}_y^\dagger$$

$$\mathbf{N} = \mathbf{N}_x \otimes \mathbf{N}_y$$

Lemma 2: $(\mathbf{A}_x \otimes \mathbf{A}_y)\mathbf{v} = \text{vec}(\mathbf{A}_x \mathbf{V} \mathbf{A}_y^\top)$, where $\mathbf{V} = \text{vec}^{-1}(\mathbf{v})$.

$$\mathbf{V} = (\mathbf{v}_1, \dots, \mathbf{v}_{n_y}) \in \mathbb{R}^{n_x \times n_y} \iff \text{vec}(\mathbf{V}) = \begin{pmatrix} \mathbf{v}_1 \\ \vdots \\ \mathbf{v}_{n_y} \end{pmatrix} \in \mathbb{R}^{n_x n_y}$$

Kronecker product and circulant matrices: Let $\mathbf{A}_x, \mathbf{A}_y$ be circulant then:

$$\begin{aligned}\mathbf{A} &= \mathbf{A}_x \otimes \mathbf{I}_y + \mathbf{I}_x \otimes \mathbf{A}_y \\ &= \mathbf{X}_x^{-1} \mathbf{D}_x \mathbf{X}_x \otimes \mathbf{X}_y^{-1} \mathbf{X}_y + \mathbf{X}_x^{-1} \mathbf{X}_x \otimes \mathbf{X}_y^{-1} \mathbf{D}_y \mathbf{X}_y \\ &= (\mathbf{X}_x^{-1} \otimes \mathbf{X}_y^{-1})(\mathbf{D}_x \otimes \mathbf{I}_y + \mathbf{I}_x \otimes \mathbf{D}_y)(\mathbf{X}_x \otimes \mathbf{X}_y) \\ &= \mathbf{X}^{-1} \mathbf{D} \mathbf{X}\end{aligned}$$

with

$$\mathbf{X} = \mathbf{X}_x \otimes \mathbf{X}_y \quad (\text{DFT matrix in 2D})$$

$$\mathbf{D} = \mathbf{D}_x \otimes \mathbf{I}_y + \mathbf{I}_x \otimes \mathbf{D}_y \quad (\text{diagonal matrix})$$

where $\mathbf{X}_x, \mathbf{X}_y$ are the DFT matrices, $\mathbf{D}_x = \text{diag}(\mathbf{X}_x \mathbf{a}_x)$, $\mathbf{D}_y = \text{diag}(\mathbf{X}_y \mathbf{a}_y)$ and $\mathbf{a}_x = \mathbf{A}_x(:, 1)$, $\mathbf{a}_y = \mathbf{A}_y(:, 1)$, respectively.

Multiplying procedure: $\mathbf{A}^\dagger \mathbf{v} := \mathbf{X}^{-1} (\mathbf{D}^\dagger (\mathbf{X} \mathbf{v}))$

$$0^\circ \quad \mathbf{d}_x := \text{fft}(\mathbf{a}_x), \mathbf{d}_y := \text{fft}(\mathbf{a}_y)$$

$$\mathbf{V} := \text{vec}^{-1}(\mathbf{v})$$

$$1^\circ \quad \mathbf{V} := \text{fft}(\mathbf{V})$$

$$2^\circ \quad \mathbf{V} := \text{fft}(\mathbf{V}^\top)^\top$$

$$3^\circ \quad \mathbf{V} := \text{vec}^{-1}(\mathbf{D}^\dagger \text{vec}(\mathbf{V}))$$

$$4^\circ \quad \mathbf{V} := \text{ifft}(\mathbf{V})$$

$$5^\circ \quad \mathbf{V} := \text{ifft}(\mathbf{V}^\top)^\top$$

$$\mathbf{A}^\dagger \mathbf{v} := \text{vec}(\mathbf{V})$$

Number of arithmetic operations :

$$\mathcal{O}(2n(\log_2 n_x + \log_2 n_y) + n) \approx \mathcal{O}(n \log_2 n), \quad n = n_x n_y$$

Multiplying procedures: $\mathbf{N}\boldsymbol{\alpha}, \mathbf{N}^\top \mathbf{v}, \mathbf{M}\boldsymbol{\alpha}, \mathbf{M}^\top \mathbf{v} \quad \dots \quad \text{analogous}$

OUTLINE

Preliminaries on saddle-point systems

Projected Schur complement method

Projected BiCGSTAB algorithm

Hierarchical multigrid

Poisson-like solver for singular matrices

Numerical experiments

$$\Omega = (0, 1) \times (0, 1)$$

$$\omega = \{(x, y) \in \mathbb{R}^2 : (x - 0.5)^2 + (y - 0.5)^2 = 0.3^2\}$$

$$\begin{cases} -\Delta u = f & \text{in } \omega \\ u = g & \text{on } \gamma \end{cases}$$

where the right hand-sides f, g are chosen appropriately to the exact solution

$$\hat{u}_{ex}(x, y) = 100((x - 0.5)^3 - (y - 0.5)^3) - x^2.$$

The auxiliary boundary Γ is obtained by shifting γ in the normal direction with

$$\delta = 8h.$$

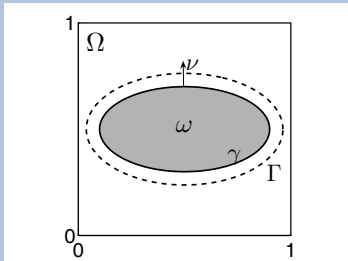


Figure 1: Geometry of ω .

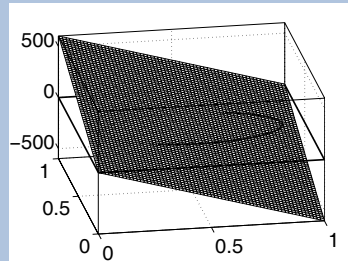


Figure 2: Right hand side f .

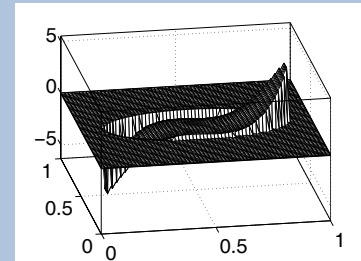


Figure 3: Ex. solution $\hat{u}_{ex}|_{\omega}$.

Classical FDM

Step h	n/m	Iters.	C.time[s]	$\text{Err}_{L^2(\omega)}$	$\text{Err}_{H^1(\omega)}$	$\text{Err}_{L^2(\partial\omega)}$
1/128	16641/35	8	0.14	2.0860e-2	1.9647e+0	6.6516e-2
1/256	66049/62	9	0.56	1.1092e-2	1.2884e+0	3.2175e-2
1/512	263169/110	12	5.19	5.3989e-3	8.6517e-1	1.5019e-2
1/1024	1050625/198	20	33.05	2.7453e-3	6.0511e-1	7.3265e-3
1/2048	4198401/360	26	167.00	1.3349e-3	4.4015e-1	3.6245e-3
Convergence rates:				0.995	0.541	1.053

New FDM, PSCM

Step h	n/m	Iters.	C.time[s]	$\text{Err}_{L^2(\omega)}$	$\text{Err}_{H^1(\omega)}$	$\text{Err}_{L^2(\partial\omega)}$
1/128	16641/35	13	0.17	2.2550e-4	1.6884e-2	1.1689e-3
1/256	66049/62	25	1.33	5.4869e-5	7.7891e-3	2.9342e-4
1/512	263169/110	40	14.97	1.4177e-5	4.0160e-3	1.1504e-4
1/1024	1050625/198	55	83.56	3.4507e-6	1.9028e-3	2.4769e-5
1/2048	4198401/360	94	571.50	9.0638e-7	9.9895e-4	1.2495e-5
Convergence rates:				1.991	1.019	1.666

New FDM, PSCM+Multigrid

Step h	n/m	Iters.	C.time[s]	$\text{Err}_{L^2(\omega)}$	$\text{Err}_{H^1(\omega)}$	$\text{Err}_{L^2(\partial\omega)}$
1/128	16641/34	11	0.22	2.4444e-4	1.8988e-2	1.4694e-3
1/256	66049/62	13	0.88	5.5030e-5	7.6303e-3	2.5171e-4
1/512	263169/110	19	8.41	1.3952e-5	3.8638e-3	8.3976e-5
1/1024	1050625/198	22	41.91	3.3209e-6	1.8681e-3	2.5253e-5
1/2048	4198401/360	31	243.50	8.5762e-7	9.6771e-4	1.1555e-5
Convergence rates:				2.036	1.062	1.730

New FDM: BiCGM - iterations, discretization error

	Classical FDM		New FDM		New FDM+Multigrid	
Step h	Iters.	$\text{Err}_{H^1(\omega)}$	Iters.	$\text{Err}_{H^1(\omega)}$	Iters.	$\text{Err}_{H^1(\omega)}$
1/128	8	1.9647e+0	13	1.6884e-2	11	1.8988e-2
1/256	9	1.2884e+0	25	7.7891e-3	13	7.6303e-3
1/512	12	8.6517e-1	40	4.0160e-3	19	3.8638e-3
1/1024	18	6.0511e-1	55	1.9028e-3	22	1.8681e-3
1/2048	25	4.4015e-1	94	9.9895e-4	31	9.6771e-4
Conv. rates:		0.54		1.02		1.06

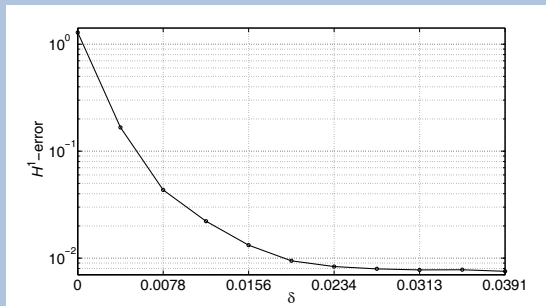


Figure 1: $H^1(\omega)$ -error sensitivity on δ .

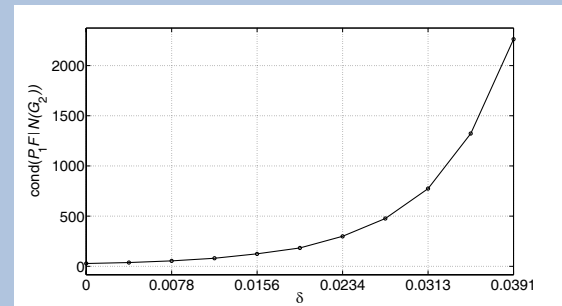


Figure 2: $\text{cond}(P_1 F|N(G_2))$ sensitivity on δ .

Conclusions

- The efficient implementation of the FDM with an auxiliary boundary.
- The saddle-point system is solved by the PSCM (non-symmetric analogy of FETI).
- The fast Poisson-like solver for singular matrices are used.
- The fast implementation is "matrix free".

References

- R. Glowinski, T. Pan, J. Periaux (1994): *A fictitious domain method for Dirichlet problem and applications*. Comput. Meth. Appl. Mech. Engrg. 111, 283–303.
- Farhat, C., Mandel, J., Roux, F., X. (1994): *Optimal convergence properties of the FETI domain decomposition method*, Comput. Meth. Appl. Mech. Engrg., 115, 365–385.
- R. K. (2005): *Complexity of an algorithm for solving saddle-point systems with singular blocks arising in wavelet-Galerkin discretizations*, Appl. Math. 50, 291–308.
- J. Haslinger, T. Kozubek, R.K., G. Peichel (2007): *Projected Schur complement method for solving non-symmetric systems arising from a smooth fictitious domain approach*, submitted in Num. Lin. Algebra Appl..
- H. A. Van der Vorst (1992): *BiCGSTAB: a fast and smoothly converging variant of BiCG for solution of nonsymmetric linear systems*, SIAM J. Sci. Statist. Comput., 13, 631–644.
- G. Meurant(1999): *Computer solution of large linear systems*, North Holland.
- M. Benzi, G. H. Golub, J. Liesen(2005): *Numerical solution of saddle point systems*, Acta Numerica, pp. 1–137.