

# The Bramble-Pasciak<sup>+</sup> preconditioner for saddle point problems

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# The linear system

## The Problem

We want to solve  $Ax = b$  where

$$\underbrace{\begin{bmatrix} A & B^T \\ B & -C \end{bmatrix}}_A \quad (1)$$

with  $A \in \mathbb{R}^{n,n}$  symmetric and positive definite and  $C \in \mathbb{R}^{m,m}$  symmetric negative semi-definite.  $B \in \mathbb{R}^{m,n}$  is assumed to have full rank.



# Saddle point problems

Saddle point problems arise in a variety of applications such as

- Mixed finite element methods for Fluid and Solid mechanics
- Interior point methods in optimisation

See Benzi, Golub, Liesen (2005), Elman, Silvester, Wathen (2005), Brezzi, Fortin (1991), Nocedal, Wright (1999)

*Saddle point problems provide due to their indefiniteness and often poor spectral properties a challenge for people developing solvers.*

Benzi, Golub, Liesen (2005)



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## Some Background – Basic relations

We introduce the bilinear form induced by  $\mathcal{H}$

$$\langle x, y \rangle_{\mathcal{H}} := x^T \mathcal{H} y$$

which is an inner product iff  $\mathcal{H}$  is positive definite. A matrix  $\mathcal{A} \in \mathbb{R}^{n \times n}$  is self-adjoint in  $\langle \cdot, \cdot \rangle_{\mathcal{H}}$  if and only if

$$\langle \mathcal{A}x, y \rangle_{\mathcal{H}} = \langle x, \mathcal{A}y \rangle_{\mathcal{H}} \quad \text{for all } x, y$$

which can be reformulated to

$$\mathcal{A}^T \mathcal{H} = \mathcal{H} \mathcal{A}.$$



## Some Background – Solvers

- CG needs symmetry in  $\langle \cdot, \cdot \rangle_{\mathcal{H}}$  **plus** positive definiteness in  $\langle \cdot, \cdot \rangle_{\mathcal{H}}$
- MINRES needs the symmetry  $\langle \cdot, \cdot \rangle_{\mathcal{H}}$  but **no** definiteness in  $\langle \cdot, \cdot \rangle_{\mathcal{H}}$

Spectral properties of  $\mathcal{A}$  can be enhanced by preconditioning, ie. considering

$$\hat{\mathcal{A}} = \mathcal{P}^{-1}\mathcal{A}$$

instead of  $\mathcal{A}$ .

Original matrix  $\mathcal{A}$  is symmetric in  $\langle \cdot, \cdot \rangle_I \Rightarrow$  MINRES can be used.

What about the symmetry of  $\hat{\mathcal{A}}$ ?



# The Bramble-Pasciak CG

We consider saddle point problem

$$\mathcal{A} = \begin{bmatrix} A & B^T \\ B & -C \end{bmatrix}$$

with a block-triangular preconditioner

$$\mathcal{P} = \begin{bmatrix} A_0 & 0 \\ B & -I \end{bmatrix}$$

which results in

$$\hat{\mathcal{A}} = \mathcal{P}^{-1}\mathcal{A} = \begin{bmatrix} A_0^{-1}A & A_0^{-1}B^T \\ BA_0^{-1}A - B & BA_0^{-1}B^T + C \end{bmatrix}.$$



# The Bramble-Pasciak CG

The preconditioned matrix

$$\hat{A} = \mathcal{P}^{-1}A = \begin{bmatrix} A_0^{-1}A & A_0^{-1}B^T \\ BA_0^{-1}A - B & BA_0^{-1}B^T + C \end{bmatrix}$$

is self-adjoint in the bilinear form defined by

$$\mathcal{H} = \begin{bmatrix} A - A_0 & 0 \\ 0 & I \end{bmatrix}.$$

Under certain conditions for  $A_0$   $\mathcal{H}$  defines an inner product and  $\hat{A}$  is also positive definite in this inner product, e.g.  $A_0 = .5A$ .

The condition for  $A_0$  usually involves the solution of an eigenvalue problem which can be expensive.





## The Bramble-Pasciak<sup>+</sup> CG

We always want an inner product for symmetric and positive definite  $A_0$

$$\mathcal{H}^+ = \begin{bmatrix} A + A_0 & \\ & I \end{bmatrix}.$$

Therefore, new preconditioner  $\mathcal{P}^+$

$$\mathcal{P}^+ = \begin{bmatrix} A_0 & 0 \\ -B & I \end{bmatrix}$$

is required. The preconditioned matrix

$$\hat{\mathcal{A}} = (\mathcal{P}^+)^{-1} \mathcal{A} = \begin{bmatrix} A_0^{-1}A & A_0^{-1}B^T \\ BA_0^{-1}A+B & BA_0^{-1}B^T - C \end{bmatrix}$$

is self-adjoint in this inner product.



## Definiteness in $\mathcal{H}^+$

If we split

$$\widehat{A}^T \mathcal{H}^+ = \begin{bmatrix} AA_0^{-1}A + A & AA_0^{-1}B^T + B^T \\ BA_0^{-1}A + B & BA_0^{-1}B^T - C \end{bmatrix}$$

as

$$\begin{bmatrix} I & \\ BA^{-1} & I \end{bmatrix} \begin{bmatrix} AA_0^{-1}A + A & \\ & -BA_0^{-1}B^T - C \end{bmatrix} \begin{bmatrix} I & A^{-1}B^T \\ & I \end{bmatrix}$$

we see that since this is a congruence transformation the matrix is always indefinite. This means:

- No reliable CG can be applied
- In practice CG quite often works fine
- Augmented methods might be used.



## An $\mathcal{H}^+$ -inner product implementation of MINRES

Use that  $\hat{A}$  symmetric in  $\mathcal{H}$ -inner product and therefore implement a version of **Lanczos process** with  $\mathcal{H}$ -inner product which gives

$$\hat{A}V_k = V_k T_k + \beta_k v_{k+1} e_k^T$$

with

$$T_k = \begin{bmatrix} \alpha_1 & \beta_1 & & & \\ \beta_1 & \ddots & \ddots & & \\ & \ddots & \ddots & \beta_{k-1} & \\ & & \beta_{k-1} & \alpha_k & \end{bmatrix} \quad \text{and } V_k = [v_1, v_2, \dots, v_k]$$

as well as  $V_k^T \mathcal{H}^+ V_k = I$ .



# An $\mathcal{H}^+$ -inner product implementation of MINRES

The following condition holds for the residual

$$\begin{aligned}\|r_k\|_{\mathcal{H}^+} &= \|b - Ax_k\|_{\mathcal{H}} = \|b - Ax_0 - AV_k y_k\|_{\mathcal{H}^+} \\ &= \|r_0 - V_{k+1} T_{k+1} y_k\|_{\mathcal{H}^+} = \|V_{k+1}(V_{k+1}^T \mathcal{H}^+ r_0 - T_{k+1} y_k)\|_{\mathcal{H}^+} \\ &= \|V_{k+1}^T \mathcal{H}^+ r_0 - T_{k+1} y_k\|_{\mathcal{H}^+} = \|\|r_0\| e_1 - T_{k+1} y_k\|_{\mathcal{H}^+}.\end{aligned}$$

Minimizing  $\|\|r_0\| e_1 - T_{k+1} y_k\|_{\mathcal{H}^+}$  can be done by the standard updated-QR factorization technique. Implementation details can be found in Greenbaum (1997).



# The simplified Lanczos method

The non-symmetric Lanczos process generates two sequences of vectors where the following condition holds

$$v_j = \phi_j(\hat{\mathcal{A}})v_1 \text{ and } w_j = \gamma_j \phi_j(\hat{\mathcal{A}}^T)w_1$$

where  $\phi$  is a polynomial of degree  $j - 1$  the so-called *Lanczos polynomial*. Setting  $w_1 = \mathcal{H}v_1$  and using the self-adjointness of  $\hat{\mathcal{A}}$  in  $\mathcal{H}^+$ , ie.  $\hat{\mathcal{A}}^T \mathcal{H}^+ = \mathcal{H}^+ \hat{\mathcal{A}}$ , gives

$$w_j = \gamma_j \phi_j(\hat{\mathcal{A}}^T)w_1 = \gamma_j \phi_j(\hat{\mathcal{A}}^T)\mathcal{H}^+v_1 = \gamma_j \mathcal{H}^+ \phi_j(\hat{\mathcal{A}})v_1 = \gamma_j \mathcal{H}^+v_j.$$

Therefore the non-symmetric Lanczos process can be simplified, ie. multiplications with  $\hat{\mathcal{A}}^T$  can be exchanged for multiplication by  $\mathcal{H}^+$ .



# The ideal transpose-free QMR method (ITFQMR)

Based on the QMR method Freund (1994) a transpose-free QMR method with an implementation derived from the BICG procedure. Here, we use matrix formulation of the non-symmetric Lanczos process

$$\hat{A}V_k = V_{k+1}H_k$$

and

$$r_k = V_{k+1}(\|r_0\| e_1 - H_k y_k).$$

Ignoring the term  $V_{k+1}$  gives QMR method. Using simplification of the Lanczos process gives ITFQMR .



## Eigenvalue analysis for $A_0 = A$

To get some insight into the convergence behaviour we the eigenvalues of

$$\hat{\mathcal{A}} = (\mathcal{P}^+)^{-1} \mathcal{A} = \begin{bmatrix} I & A^{-1}B^T \\ 2B & BA^{-1}B^T \end{bmatrix}.$$

For the eigenpair  $(\lambda, \begin{bmatrix} x \\ y \end{bmatrix})$  of  $\hat{\mathcal{A}}$  we know that

$$\begin{bmatrix} I & A^{-1}B^T \\ 2B & BA^{-1}B^T \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x + A^{-1}B^T y \\ 2Bx + BA^{-1}B^T y \end{bmatrix} = \lambda \begin{bmatrix} x \\ y \end{bmatrix}$$

For  $\lambda = 1$  we get

$$Ax + B^T y = Ax$$

which gives  $B^T y = 0$  and  $y = 0$  iff  $Bx = 0$ .

Since  $\dim(\ker(B)) = n - m$  multiplicity of  $\lambda = 1$  is  $n - m$ .



## Eigenvalue analysis for $A_0 = A$

For  $\lambda \neq 1$ , we get that  $x = \frac{1}{\lambda-1}A^{-1}B^T y$  which gives

$$BA^{-1}B^T y = \frac{\lambda(\lambda-1)}{\lambda+1}y.$$

For an eigenvalue  $\sigma$  of  $BA^{-1}B^T$  we get

$$\sigma = \frac{\lambda(\lambda-1)}{\lambda+1}.$$

Eigenvalues of  $\hat{A}$  become

$$\lambda_{1,2} = \frac{1+\sigma}{2} \pm \sqrt{\frac{(1+\sigma)^2}{4} + \sigma}.$$

Since  $\sigma > 0$  we have  $m$  negative eigenvalues.





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# Numerical Experiments – Stokes problem

We are going to solve saddle point systems coming from the finite element method for the Stokes problem

$$\begin{aligned} -\nabla^2 \mathbf{u} + \nabla p &= 0 \\ \nabla \cdot \mathbf{u} &= 0 \end{aligned}$$

The linear system governing the finite element method for the Stokes problem is a saddle point problem

$$\begin{bmatrix} A & B^T \\ B & -C \end{bmatrix}$$

where  $C \neq 0$  for stabilized systems. In our examples  $C = 0$ .

All examples come from the IFISS package.



# Block diagonal preconditioning

Silvester and Wathen (1993,1994) use preconditioner

$$\mathcal{P} = \begin{bmatrix} A_0 & 0 \\ 0 & S_0 \end{bmatrix}$$

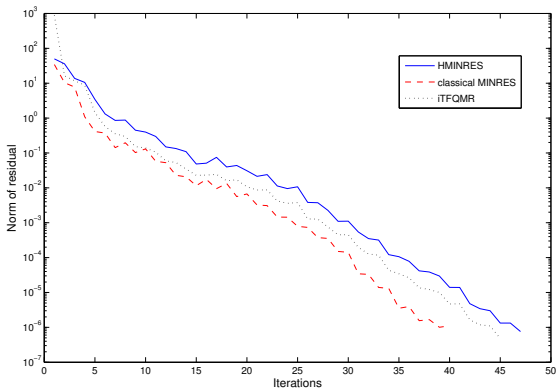
which is symmetric positive definite.

$\implies$  Preconditioned MINRES can be applied.



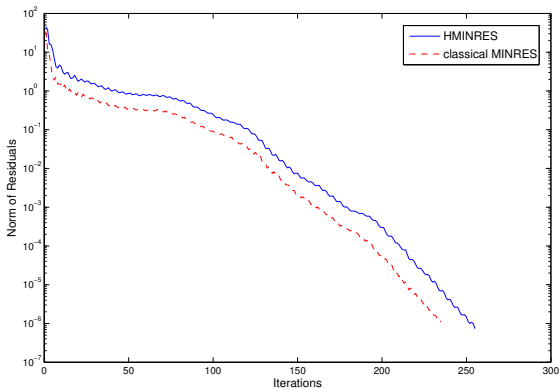
# Example 1 – Stokes problem Channel domain

Results for  $\mathcal{H}$ -MINRES and classical Preconditioned MINRES with problem dimension 9539. Preconditioner  $A_0 = A$  and  $S_0$  being the Gramian (Mass matrix).



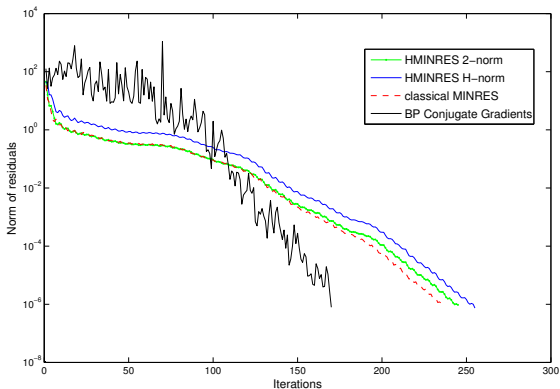
## Example 2 – Stokes problem Channel domain

Results for  $\mathcal{H}$ -MINRES and classical Preconditioned MINRES with problem dimension 9539. Preconditioner  $A_0$  is Incomplete Cholesky of  $A$  and  $S_0$  being the Gramian (Mass matrix).



## Example 3 – Stokes problem Channel domain

Again  $\mathcal{H}$ -MINRES and classical Preconditioned MINRES for problem dimension 9539. Preconditioner  $A_0$  is Incomplete Cholesky of  $A$  and  $S_0$  being the Gramian (Mass matrix). Additionally,  $\mathcal{H}$ -MINRES residual in the 2-norm and the classical Bramble-Pasciak CG.



# Conclusions

- We presented an alternative approach
- Method could be used with augmented techniques to become competitive
- Presented algorithm could be used for combination preconditioning





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**Thank you for your attention!**

**Difficult questions can be discussed in 20 minutes in the pub!**

