# GMRES preconditioned by a perturbed $L D L^{T}$ decomposition with static pivoting 

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## Outline

- Multifrontal
- Static pivoting
-GMRES and Flexible GMRES
■ Flexible GMRES: a roundoff error analysis
■ GMRES right preconditioned: a roundoff error analysis
■ Numerical experiments


## Linear system

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$\mathrm{Ax}=\mathrm{b}$

## where $\mathbf{A} \in \mathbf{R}^{n \times n}$

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We wish to solve large sparse systems
$\mathbf{A x}=\mathbf{b} \quad$ where $\mathbf{A} \in \mathbf{R}^{n \times n}$
$\mathbf{A}=\left[\begin{array}{ll}H & B \\ B^{T} & 0\end{array}\right]$

## Multifrontal method

## ASSEMBLY TREE



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AT EACH NODE


## Multifrontal method

## ASSEMBLY TREE



## AT EACH NODE



$$
F_{22} \leftarrow F_{22}-F_{12}^{T} F_{11}^{-1} F_{12}
$$

Pivoting ( $1 \times 1$ )


Choose $x$ as $1 \times 1$ pivot if $|x|>u|y|$ where $|y|$ is the largest in column.

Pivoting (2 $\times 2$ )


For the indefinite case, we can choose $2 \times 2$ pivot where we require

$$
\left|\left[\begin{array}{ll}
x_{1} & x_{2} \\
x_{2} & x_{3}
\end{array}\right]^{-1}\right|\left[\begin{array}{l}
|y| \\
|z|
\end{array}\right] \leq\left[\begin{array}{c}
\frac{1}{u} \\
\frac{1}{u}
\end{array}\right]
$$

where again $|y|$ and $|z|$ are the largest in their columns.

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- DELAY the pivot and then send to the parent a larger Schur complement.


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■ we can either take the RISK and use it or
DELAY the pivot and then send to the parent a larger Schur complement.
This can cause more work and storage

## Static Pivoting

An ALTERNATIVE is to use Static Pivoting, by replacing $x_{k}$ by

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x_{k}+\tau
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and CONTINUE.

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This is even more important in the case of parallel implementation where static data structures are often preferred

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x_{k}+\tau
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and CONTINUE.
Several codes use (or have an option for) this device:
■SuperLU (Demmel and Li)
$■$ PARDISO (Gärtner and Schenk)

- MA57 (Duff and Pralet)


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and CONTINUE.
We thus have factorized

$$
A+E=L D L^{T}=M
$$

where $|E| \leq \tau I$
The three codes then have an Iterative Refinement option.
IR will converge if $\rho\left(M^{-1} E\right)<1$

## Roundoff error 1

The computed $\hat{L}$ and $\hat{D}$ in floating-point arithmetic satisfy

$$
\left\{\begin{array}{l}
A+\delta A+\tau E=M \\
\|\delta A\| \leq c(n) \varepsilon\left\||\hat{L}||\hat{D}|\left|\hat{L}^{T}\right|\right\| \\
\|E\| \leq 1
\end{array}\right.
$$

The perturbation $\delta A$ must have a norm smaller than $\tau$, in order to not dominate the global error.

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A sufficient condition for this is

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\begin{array}{|l|}
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\hline
\end{array}
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\hline n \varepsilon||\hat{L}|| \hat{L}^{T}| | \\
\hline
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$$

$\||\hat{L}||\hat{D}|\left|\hat{L}^{T}\right|| | \approx \frac{n}{\tau} \Longrightarrow \varepsilon \leq \frac{\tau^{2}}{n^{2}}$

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In real life $\rho\left(M^{-1} E\right)>1$

## Right preconditioned GMRES and Flexible GMRES

procedure $[\mathrm{x}]=$ right_Prec_GMRES(A,M,b)

$$
\begin{aligned}
& x_{0}=M^{-1} b, r_{0}=b-A x_{0} \text { and } \beta=\left\|r_{0}\right\| \\
& v_{1}=r_{0} / \beta ; \mathrm{k}=0 \\
& \text { while }\left\|r_{k}\right\|>\mu\left(\|b\|+\|A\|\left\|x_{k}\right\|\right) \\
& \quad k=k+1 ; \\
& z_{k}=M^{-1} v_{k} ; w=A z_{k} ; \\
& \text { for } i=1, \ldots, k \text { do } \\
& \quad h_{i, k}=v_{i}^{T} w ; \\
& \quad w=w-h_{i, k} v_{i} \\
& \quad \text { end for; } \\
& \quad h_{k+1, k}=\|w\| ; \\
& \quad v_{k+1}=w / h_{k+1, k} ; \\
& V_{k}=\left[v_{1}, \ldots, v_{k}\right] \\
& H_{k}=\left\{h_{i, j}\right\}_{1 \leq i \leq j+1 ; 1 \leq j \leq k} ; \\
& y_{k}=\arg \min y\left\|\beta e_{1}-H_{k} y\right\| ; \\
& x_{k}=x_{0}+M_{1}-1 V_{k} y_{k} \text { and } r_{k}=b-A x_{k} ;
\end{aligned}
$$

end procedure.
procedure $[\mathrm{x}]=\operatorname{FGMRES}\left(\mathrm{A}, M_{i}, \mathrm{~b}\right)$

$$
\begin{aligned}
& x_{0}=M_{0}^{-1} b, r_{0}=b-A x_{0} \text { and } \beta=\left\|r_{0}\right\| \\
& v_{1}=r_{0} / \beta ; \mathrm{k}=0 ; \\
& \text { while }\left\|r_{k}\right\|>\mu\left(\|b\|+\|A\|\left\|x_{k}\right\|\right) \\
& \quad k=k+1 ; \\
& \quad z_{k}=M_{k}^{-1} v_{k} ; w=A z_{k} ; \\
& \quad \text { for } i=1, \ldots, k \text { do } \\
& \quad h_{i, k}=v_{i}^{T} w ; \\
& \quad w=w-h_{i, k} v_{i} \\
& \quad \text { end for; } \\
& \quad h_{k+1, k}=\|w\| ; \\
& \quad v_{k+1}=w / h_{k+1, k} ; \\
& \quad Z_{k}=\left[z_{1}, \cdots, z_{k}\right] ; V_{k}=\left[v_{1}, \ldots, v_{k}\right] \\
& H_{k}=\left\{h_{i, j}\right\}_{1 \leq i \leq j+1 ; 1 \leq j \leq k} \\
& \quad y_{k}=\arg \min _{y}\left\|\beta e_{1}-H_{k} y\right\| ; \\
& \quad x_{k}=x_{0}+Z_{k} y_{k} \text { and } r_{k}=b-A x_{k}
\end{aligned}
$$

end procedure.

## Roundoff error FGMRES

Theorem 1.

$$
\sigma_{\min }\left(\bar{H}_{k}\right)>c_{7}(k, 1) \varepsilon\left\|\bar{H}_{k}\right\|+\mathcal{O}\left(\varepsilon^{2}\right) \quad \forall k,
$$

$$
\left|\bar{s}_{k}\right|<1-\varepsilon, \forall k
$$

(where $\bar{s}_{k}$ are the sines computed during the Givens algorithm)
and

$$
2.12(n+1) \varepsilon<0.01 \text { and } 18.53 \varepsilon n^{\frac{3}{2}} \kappa\left(C^{(k)}\right)<0.1 \forall k
$$

$$
\exists \hat{k}, \quad \hat{k} \leq n
$$

such that, $\forall k \geq \hat{k}$, we have
$\left\|b-A \bar{x}_{k}\right\| \leq c_{1}(n, k) \varepsilon\left(\|b\|+\|A\|\left\|\bar{x}_{0}\right\|+\|A\|\left\|\bar{Z}_{k}\right\|\left\|\bar{y}_{k}\right\|\right)+\mathcal{O}\left(\varepsilon^{2}\right)$.

## Roundoff error FGMRES

Moreover, if $M_{i}=M, \forall i$,

$$
\rho=1.3\left\|\hat{W}_{k}\right\|+c_{2}(k, 1) \varepsilon\|M\|\left\|\bar{Z}_{k}\right\|<1 \quad \forall k<\hat{k},
$$

where

$$
\hat{W}_{k}=\left[M \bar{z}_{1}-\bar{v}_{1}, \ldots, M \bar{z}_{k}-\bar{v}_{k}\right],
$$

we have:

$$
\left\|b-A \bar{x}_{k}\right\| \leq c(n, k) \gamma \varepsilon\left(\|b\|+\|A\|\left\|\bar{x}_{0}\right\|+\|A\|\left\|\bar{Z}_{k}\right\|\left\|M\left(\bar{x}_{k}-\bar{x}_{0}\right)\right\|\right)+\mathcal{O}\left(\varepsilon^{2}\right)
$$

$$
\gamma=\frac{1.3}{1-\rho}
$$

Giraud and Langou, Björck and Paige, and generalise Paige, Rozložník, and Strakoš

## Roundoff error FGMRES

## Theorem 2

Under the Hypotheses of Theorem 1, and

$$
\mathbf{c}(n) \varepsilon\left\||\hat{L}||\hat{D}|\left|\hat{L}^{T}\right|\right\|<\tau
$$

$$
c(n, k) \gamma \varepsilon\|A\|\left\|\bar{Z}_{k}\right\|<1 \quad \forall k<\hat{k}
$$

$$
\max \left\{\left\|M^{-1}\right\|,\left\|\bar{Z}_{k}\right\|\right\} \leq \frac{\tilde{c}}{\tau}
$$

we have

## Roundoff error FGMRES

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$$

$$
c(n, k) \gamma \varepsilon\|A\|\left\|\bar{Z}_{k}\right\|<1 \quad \forall k<\hat{k}
$$

$$
\max \left\{\left\|M^{-1}\right\|,\left\|\bar{Z}_{k}\right\|\right\} \leq \frac{\tilde{c}}{\tau}
$$

we have

$$
\begin{gathered}
\left\|b-A \bar{x}_{k}\right\| \leq 2 \mu \varepsilon\left(\|b\|+\|A\|\left(\left\|\bar{x}_{0}\right\|+\left\|\bar{x}_{k}\right\|\right)\right)+\mathcal{O}\left(\varepsilon^{2}\right) . \\
\mu=\frac{c(n, k)}{1-c(n, k) \varepsilon\|A\|\left\|\bar{Z}_{k}\right\|}
\end{gathered}
$$

## Roundoff error right preconditioned GMRES

Theorem 3
We assume of applying Iterative Refinement for solving $M\left(\bar{x}_{k}-\bar{x}_{0}\right)=\bar{V}_{k} \bar{y}_{k}$ at last step.
Under the Hypotheses of Theorem 1 and $c(n) \varepsilon \kappa(M)<1$

$$
\exists \hat{k}, \quad \hat{k} \leq n
$$

such that, $\forall k \geq \hat{k}$, we have

$$
\begin{aligned}
\left\|b-A \bar{x}_{k}\right\| \leq & c_{1}(n, k) \varepsilon\left\{\|b\|+\|A\|\left\|\bar{x}_{0}\right\|+\|A\|\left\|\bar{Z}_{k}\right\|\left\|M\left(\bar{x}_{k}-\bar{x}_{0}\right)\right\|+\right. \\
& \left\|A M^{-1}\right\|\|\|M\|\| \bar{x}_{k}-\bar{x}_{0} \|+ \\
& \left\|A M^{-1}\right\|\left\|\left|\left\|\hat{L}||\hat{D}|| \hat{L}^{T} \mid\right\|\left\|M\left(\bar{x}_{k}-\bar{x}_{0}\right)\right\|\right\}+\mathcal{O}\left(\varepsilon^{2}\right) .\right.
\end{aligned}
$$

## MA57 tests

|  | n | nnz | nnz(L)+nnz(D) | Fact. time |
| :---: | ---: | ---: | ---: | :---: |
| CONT_201 | 80595 | 239596 | 9106766 | 9.0 sec |
| CONT_300 | 180895 | 562496 | 22535492 | 28.8 sec |

MA57 without static pivot

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|  | nnz(L)+nnz(D)+ <br> FGMRES (\#it) | Fact. time | \# static pivots |
| :--- | ---: | ---: | ---: |
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MA57 with static pivot $\tau=10^{-8}$

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MA57 with static pivot $\tau=10^{-8}$
IR does not converge!

## Numerical experiments



FGMRES on CONT-300 test example

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■IR with static pivoting is very sensitive to $\tau$ and not robust
■ GMRES is also sensitive and not robust
$\square$ FGMRES is robust and less sensitive (see roundoff analysis)
■ Gains from restarting. Makes GMRES more robust, saves storage in FGMRES ( but not really needed)

