Master of Science on Computational Science

Institute of Computational Science

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29 Oct 2015, LAB7

The linear system

After discretization in space or space and time we end up with

$$A x = b$$
, or in the time dependent case,
 $A_n x_n = b_n$

Solution techniques

- Direct sparse methods
- Iterative methods

Direct sparse solvers

Complexity in 2D

- $O(N^{1.5})$ factorization
- $O(N \log N)$ solution

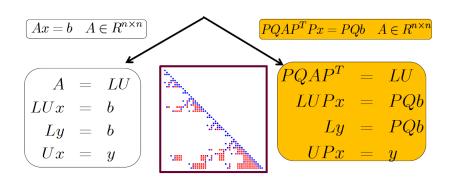
Complexity in 3D

- $O(N^2)$ factorization
- $O(N^{1.5})$ solution

Available Software

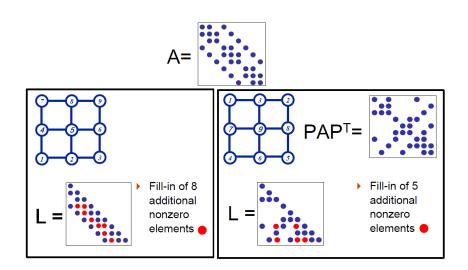
- PARDISO
- UMFPACK, CHOLMOD
- SUPERLU
- MUMPS

Efficient linear algebra

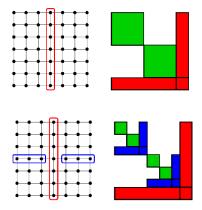


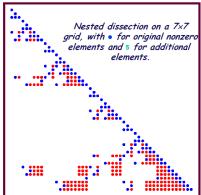
- Permutations P and Q chosen to preserve **sparsity** and **maintain** stability in PAQ = LU.
- L = Lower triangular, U = Upper triangular (sparse)

Nested dissection permutation P



Nested dissection ordering on a 7×7 grid





Direct Sparse Solvers

PARDISO performance in 2D

mesh	El	memory			
nodes	init	fact	back-sub	total	MB
65175	0.704	0.265	0.019	0.988	26.0
263838	3.199	1.539	0.111	4.849	117.5
1068112	14.766	9.518	0.535	24.819	527.7

PARDISO performance in 3D

mesh	E	memory			
nodes	init	fact	back-sub	total	MB
32002	0.636	2.783	0.069	3.488	80.4
256011	6.925	185.469	1.428	193.8	1438.3
2000396	76.625	11762.1	21.46	11860	24403.0

Iterative Krylov subspace methods

They work with matrix-vector products Ay for given vectors y

Symmetric systems

- PCG
- MINRES
- SYMMLQ
- LSMR.
- SQMR

Nonsymmetric systems

- GMRES
- CGS
- BICGSTAB
- QMR
- LSQR

Preconditioners

$$A x = b$$

left:
$$P^{-1}A x = P^{-1}b$$

right: $AP^{-1}y = b$, Px = y

Iterative Krylov subspace methods

At each timestep of the simulation whether we solve linear or nonlinear PDEs we need to solve until convergence one or several linear systems:

At the *n*th timestep

$$A_n x_n = b_n$$

Left preconditioning

$$P_n^{-1}(A_n \ x_n) = P_n^{-1} \ b_n$$

High condition number

Lower condition number

Iterative Krylov subspace methods require only matrix-vector products Ay for given vectors y and depending on the type of the matrix we have

Symmetric matrices

- PCG
- MINRES

Nonsymmetric matrices

- GMRES
- BICGSTAB

Generalized minimum residual methods

GMRES(A,M,b,tol)

$$x_0 = M^{-1}b, r_0 = b - Ax_0,$$

 $\beta = ||r_0||_2 u_1 = \frac{r_0}{\beta}, k = 0$
while $||r_k||_2 > \beta \text{ tol}$
 $k = k + 1 z_k = M^{-1}v_k, w = Az_k$

for
$$i = 1, 2, ..., k$$
 do

$$h_{i,k} = u_i^T w, \ w = w - h_{i,k} u_i$$

end for

$$h_{k+1,k} = ||w||_2, \ u_{k+1} = \frac{w}{h_{k+1,k}}$$

$$V_k = [v_1, \dots, v_k]$$

$$H_k = \{h_{i,j}\}, \ 1 \le i \le j+1, \ 1 \le j \le k$$

$$y_k = \operatorname{argmin}_y \|\beta e_1 - H_k y\|_2$$

$$x_k = x_0 + M^{-1}V_k y_k, r_k = b - A x_k$$

end while

FGMRES(A,M,b,tol)

$$x_0 = M_0^{-1}b, \ r_0 = b - Ax_0,$$

$$\beta = ||r_0||_2 \ u_1 = \frac{r_0}{\beta}, \ k = 0$$

while
$$||r_k||_2 > \beta \ tol$$

$$k = k + 1, z_k = M_k^{-1} v_k, \ w = A z_k$$

for
$$i = 1, 2, \dots, k$$
 do

$$h_{i,k} = u_i^T w, \ w = w - h_{i,k} u_i$$

end for

$$h_{k+1,k} = ||w||_2, \ u_{k+1} = \frac{w}{h_{k+1,k}}$$

$$V_k = [v_1, \dots, v_k], \ Z_k = [z_1, \dots, z_k]$$

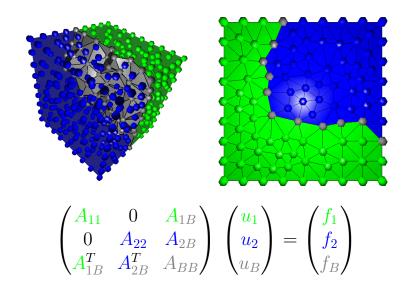
$$H_k = \{h_{i,j}\}, \ 1 \le i \le j+1, \ 1 \le j \le k$$

$$y_k = \operatorname{argmin}_y \|\beta e_1 - H_k y\|_2$$

$$x_k = x_0 + Z_k y_k, \ r_k = b - A x_k$$

end while

Preconditioning methods: domain decomposition



Preconditioning methods: multigrid

Multigrid methods

- Geometric MG
- Algebraic MG

Software

- PETSc
- SAMG/XAMG