

Introduction to 3-D finite element computation

Atsushi Suzuki

KM FJFI CVUT

Faculty of Mathematics, Kyushu University

`asuzuki@math.kyushu-u.ac.jp`

Linear solvers for the system of the sparse matrix.

- linear equations
- direct method
 - LDL^T factorization
- iterative method
 - CG
 - Preconditioned CG
 - GMRES
- treatment of essential boundary conditions
 - Lagrange multiplier
 - orthogonal projection

Finite element equation (1/2)

bilinear form and functional:

$$a(u, v; \Omega) = 2\mu \int_{\Omega} \sum_{1 \leq i, j \leq 3} [\epsilon(u)]_{ij} [\epsilon(v)]_{ij} dx + \lambda \int_{\Omega} \operatorname{div} u \operatorname{div} v dx,$$

$$l(v; \Omega) = \int_{\Omega} f \cdot v dx + \int_{\Gamma_N} h \cdot v ds$$

affine space and subspace:

$$V_h(g) := \{v_h \in Y_h; v_h(P_\alpha) = g(P_\alpha) \quad \forall \alpha \in \Lambda_D\}$$

$$V_h := V_h(0) = \{v_h \in Y_h; v_h(P_\alpha) = 0 \quad \forall \alpha \in \Lambda_D\}$$

finite element equation:

Find $u_h \in V_h(g)$ such that

$$a(u_h, v_h) = l(v_h) \quad \forall v_h \in V_h$$

Finite element equation (2/2)

stiffness matrix:

$$[A]_{\alpha\beta} = a(\varphi_\beta, \varphi_\alpha)$$

right-hand vector

$$[b]_\alpha = l(\varphi_\alpha) - \sum_{\beta \in \Lambda_D} a(\varphi_\beta, \varphi_\alpha) g_\beta \quad (\alpha \in \Lambda_Y \setminus \Lambda_D)$$

$(N_Y - N_D) \times (N_Y - N_D)$ stiffness matrix: symmetric positive definite (SPD)

$$[A]_{\alpha\beta} = [A]_{\beta\alpha}, \quad (Au, u) > 0 \quad (\forall u \in \mathbb{R}^{N_Y - N_D}).$$

positive definiteness \Leftrightarrow coercivity of $a(\cdot, \cdot)$

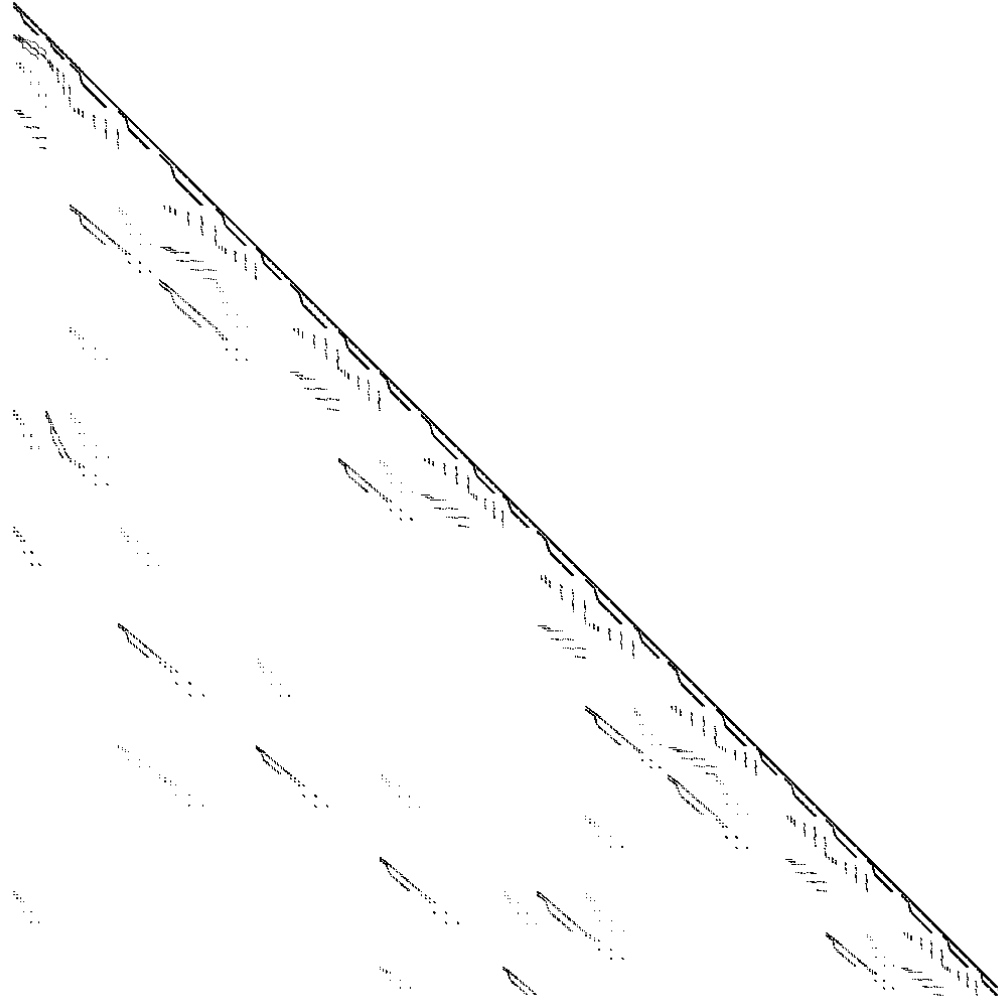
$A : N \times N$ SPD matrix

$b : N$ vector

How to find $x \in \mathbb{R}^N$ satisfying $Ax = b$?

Sparse matrix

lower triangle part of symmetric stiffness matrix



$$N_G = 4,692$$

$$N_A = 34,126 \text{ (nonzeros = nnz)}$$

$$\text{max of nonzeros in the row} = 20.$$

Direct solver : LDL^T factorization (1/6)

$A : N \times N$ SPD matrix

$$A = L D L^T$$

L : lower triangular matrix, $[L]_{ij} = 0$ ($i < j$), $[L]_{ii} = 1$,

D : diagonal matrix,

the factorization is unique.

Direct solver : LDL^T factorization (2/6)

$A : N \times N$ SPD matrix

$$A = L D L^T$$

L : lower triangular matrix, $[L]_{ij} = 0$ ($i < j$), $[L]_{ii} = 1$,

D : diagonal matrix,

$A^{(k)}$: $k \times k$ -sub matrix of A ,

$L^{(k-1)} \in \mathbb{R}^{(k-1) \times (k-1)}$: $(k-1) \times (k-1)$ -sub matrix of L ,

$l = [l_{k1} \ l_{k2} \ \dots \ l_{kk-1}]^T \in \mathbb{R}^{(k-1)}$

$$\begin{aligned} A^{(k)} &= \begin{bmatrix} L^{(k-1)} & 0 \\ l^T & 1 \end{bmatrix} \begin{bmatrix} D^{(k-1)} & 0 \\ 0 & d_{kk} \end{bmatrix} \begin{bmatrix} L^{(k-1)T} & l \\ 0 & 1 \end{bmatrix} \\ &= \begin{bmatrix} L^{(k-1)} D^{(k-1)} L^{(k-1)T} & L^{(k-1)} D^{(k-1)} l \\ l^T D^{(k-1)} L^{(k-1)T} & l^T D^{(k-1)} l + d_{kk} \end{bmatrix} \end{aligned}$$

Direct solver : LDL^T factorization (3/6)

$$\begin{aligned} A^{(k)} &= \begin{bmatrix} L^{(k-1)} & 0 \\ l^T & 1 \end{bmatrix} \begin{bmatrix} D^{(k-1)} & 0 \\ 0 & d_{kk} \end{bmatrix} \begin{bmatrix} L^{(k-1)T} & l \\ 0 & 1 \end{bmatrix} \\ &= \begin{bmatrix} L^{(k-1)} D^{(k-1)} L^{(k-1)T} & L^{(k-1)} D^{(k-1)} l \\ l^T D^{(k-1)} L^{(k-1)T} & l^T D^{(k-1)} l + d_{kk} \end{bmatrix} \end{aligned}$$

find $\{l_{ij}\}_{1 \leq j < i \leq N}$ and $\{d_{kk}\}_{1 \leq k \leq N}$

$$\begin{bmatrix} a_{k1} \\ a_{k2} \\ \vdots \\ a_{kk-1} \end{bmatrix} = L^{(k-1)} D^{(k-1)} \begin{bmatrix} l_{k1} \\ l_{k2} \\ \vdots \\ l_{kk-1} \end{bmatrix}$$

$$a_{kk} = l^T D^{(k-1)} l + d_{kk}$$

Direct solver : LDL^T factorization (4/6)

Algorithm: LDL^T factorization

do $k = 1, 2, \dots, N$

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

$$l_{ki}d_{ii} = a_{ki} - \sum_{j=1}^{i-1} l_{ij}d_{jj}l_{kj}$$

enddo

$$d_{kk} = a_{kk} - \sum_{j=1}^{k-1} l_{kj}d_{jj}l_{kj}$$

envelop method

Direct solver : LDL^T factorization (5/6)

Algorithm: LDL^T factorization

do $k = 1, 2, \dots, N$

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

$$\lambda_{ki} = a_{ki} - \sum_{j=1}^{i-1} l_{ij} \lambda_{kj}$$

$$l_{ki} = \lambda_{ki} / d_{ii}$$

enddo

$$d_{kk} = a_{kk} - \sum_{j=1}^{k-1} l_{kj} \lambda_{kj}$$

Direct solver : LDL^T factorization (6/6)

To find x satisfying $LDL^T x = b$,

$$Ly = b$$

$$DL^T = y$$

are solved sequentially.

A : sparse $\Rightarrow LDL^T$ factorization is only needed on some nonzero components.

fill-in : components with 0 become nonzeros during factorization

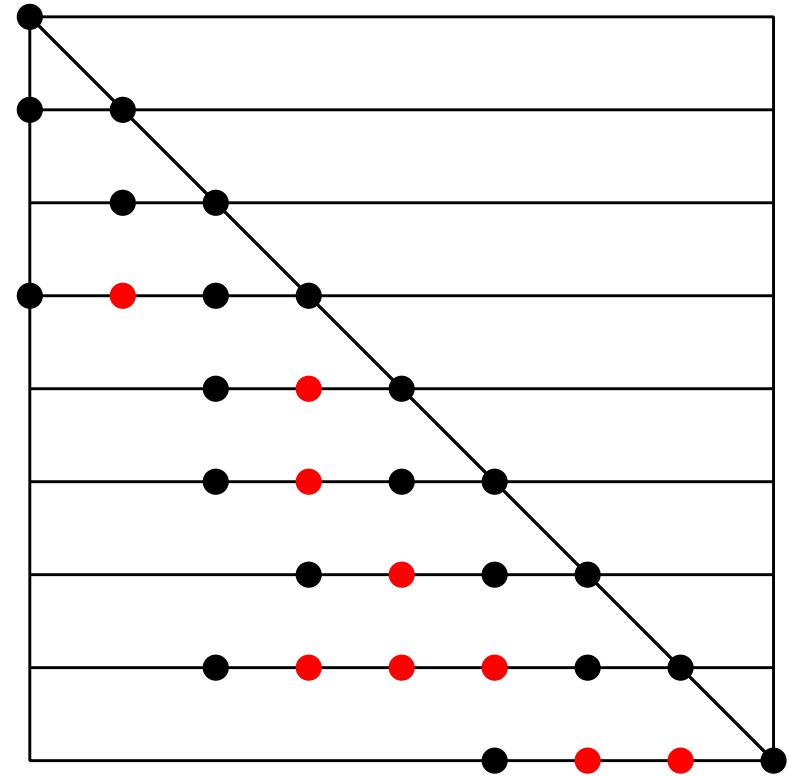
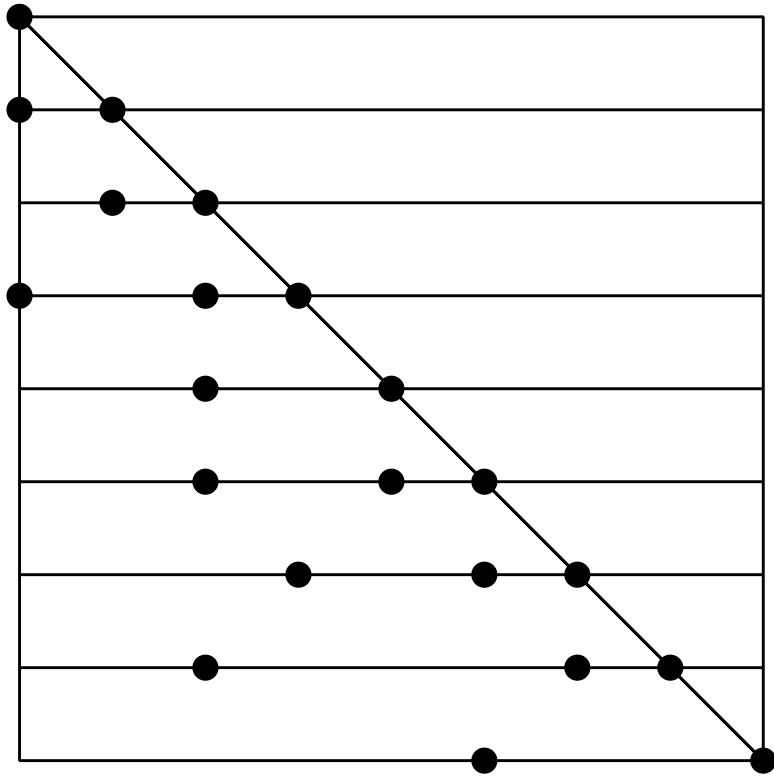
SKS (Skyline Storage) : factorization begins with the minimum column index of nonzero in a row

ordering : technique to reduce fill-in by renumbering of nodes

Skyline Storage (SKS) format

minimum column index of nonzero index on k -th row:

$$\beta(\mu) = \min\{\nu \in \{1, 2, \dots, N\}; [A]_{\mu\nu} \neq 0\}$$



$$v_A^S \in \mathbb{R}^{N_A^{(S)}}, \quad \beta \in \mathbb{R}^{N_G}, \quad N_A^{(S)} = \sum_{1 \leq \mu \leq N_G} (\mu - \beta[\mu] + 1)$$

$$v_A^S[k] = A_{\mu\nu}, \quad \beta[\mu] \leq \nu \leq \mu,$$

$$\sum_{1 \leq \nu < \mu} (\nu - \beta[\nu] + 1) < k \leq \sum_{1 \leq \nu \leq \mu} (\nu - \beta[\nu] + 1)$$

Incomplete LDL^T factorization with SKS

minimum column index of nonzero index on k -th row:

$$\beta(k) = \min\{\mu \in \{1, 2, \dots, N\}; [A]_{k\mu} \neq 0\}$$

Algorithm:

do $k = 1, 2, \dots, N$

do $i = \beta(k), \dots, k - 1$

$$\lambda_{ki} = a_{ki} - \sum_{j=\max(\beta(k), \beta(i))}^{i-1} l_{ij} \lambda_{kj}$$

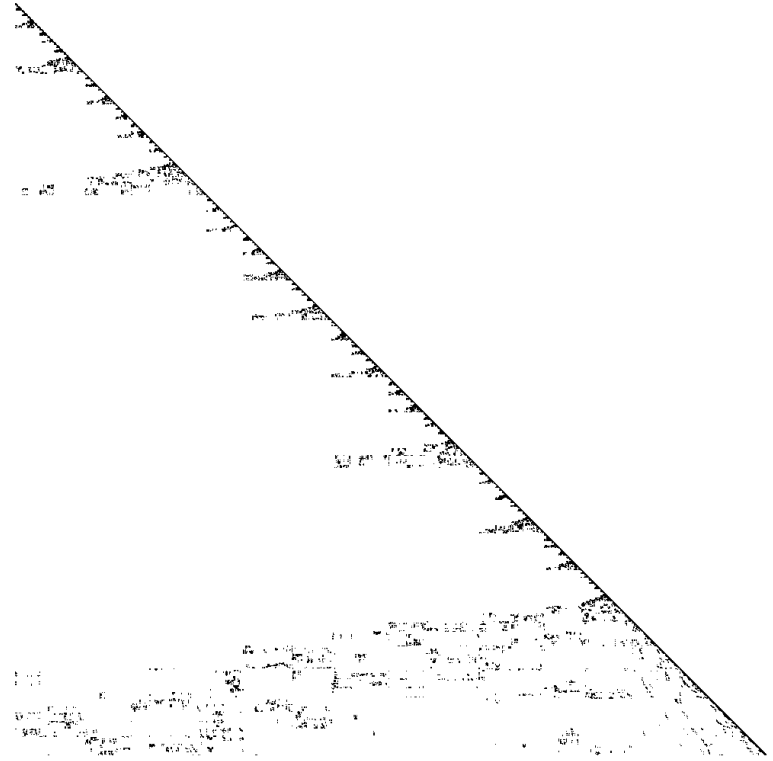
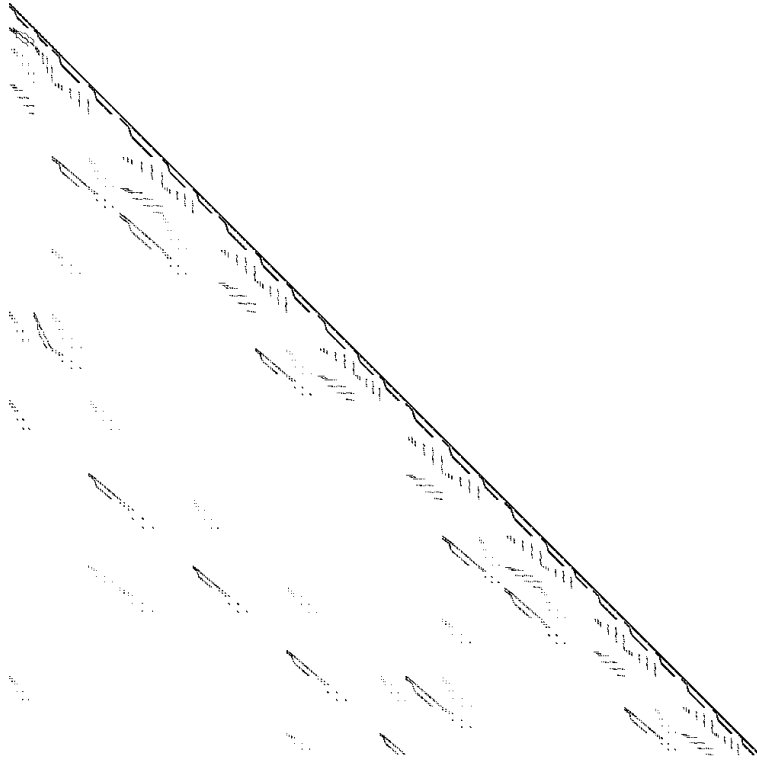
$$l_{ki} = \lambda_{ki} / d_{ii}$$

enddo

$$d_{kk} = a_{kk} - \sum_{j=\max(\beta(k), \beta(i))}^{i-1} l_{kj} \lambda_{kj}$$

An example of ordering

lower triangle part of symmetric stiffness matrix



AMD : An approximate minimum degree ordering

$$N_G = 4,692$$

$$N_A = 34,126 \text{ (nonzeros = nnz)}$$

total memory for elasticity solver: 344.4M \rightarrow 235.1M.

Direct solver : LU factorization

for unsymmetric matrix:

$$\begin{aligned} A^{(k)} &= \begin{bmatrix} L^{(k-1)} & 0 \\ l^T & 1 \end{bmatrix} \begin{bmatrix} U^{(k-1)T} & u \\ 0 & d_{kk} \end{bmatrix} \\ &= \begin{bmatrix} L^{(k-1)}U^{(k-1)T} & L^{(k-1)}u \\ l^T L^{(k-1)T} & l^T u + d_{kk} \end{bmatrix} \end{aligned}$$

find $\{l_{ij}\}_{1 \leq j < i \leq N}$, $\{u_{ji}\}_{1 \leq j < i \leq N}$, and $\{d_{kk}\}_{1 \leq k \leq N}$.

In envelope method l and u are stored with SKS format.

Stiffness matrix of finite element has symmetric pattern of nonzeros.

Development of direct solver for sparse matrix

Direct solver for fast computation

- ordering : Reverse Cuthill-McKee, Minimum degree

- factorization :

UMFPACK T. Davis, 1997

SuperLU X. Li, 1999

PARDISO O. Schenk, 2000 ∈ Intel compiler

- parallelization for SMP : SuperLU, PARDISO

large scale problem → Krylov subspace methods

Iterative solver : CG method (1/3)

$x_0 \rightarrow x_1 \rightarrow x_2 \rightarrow \dots \rightarrow x_m \rightarrow \dots$ (iteratively)

Krylov subspace

$$K_n(A, r) := \text{span}[r, A r, A^2 r, \dots, A^{n-1} r]$$

$\dim K_n(A, r) \leq N$, depends on $r \in \mathbb{R}^N$.

$$M = \min\{n; K_n(A, r) = K_{n+1}(A, r)\}$$

$$K_1(A, r) \subset K_2(A, r) \subset \dots \subset K_M(A, r) = K_{M+1}(A, r) = \dots$$

$x_0 \in \mathbb{R}^N$: initial guess, $r_0 = b - A x_0$: initial residual

CG method finds $u_n \in K_n(A, r_0)$ satisfying

$$(A(x_0 + u_n), y) = (b, y) \quad \forall y \in K_n(A, r_0).$$

A : SPD \Rightarrow unique solution exists in each Krylov subspace

$$K_n(A, r_0) \quad (1 \leq n \leq M).$$

Iterative solver : CG method (2/3)

Algorithm : CG method

$$x_0 \in \mathbb{R}^N ,$$

$$r_0 := b - Ax_0 ,$$

$$p_0 := r_0 ,$$

do $n = 0, 1, \dots$, until $\|r_n\| / \|r_0\| < \varepsilon$

$$\alpha_n := (r_n, r_n) / (Ap_n, p_n) ,$$

$$x_{n+1} := x_n + \alpha_n p_n ,$$

$$r_{n+1} := r_n - \alpha_n Ap_n ,$$

$$\beta_n := (r_{n+1}, r_{n+1}) / (r_n, r_n) ,$$

$$p_{n+1} := r_{n+1} + \beta_n p_n .$$

$\varepsilon > 0$: stopping criteria

Iterative solver : CG method (3/3)

CG minimizes the functional $J(u) = \frac{1}{2}(Au, u) - (b, u)$ on $K_n(A, r_0) + x_0$.

the minimizer $x_n \in K_n(A, r_0) + x_0$:

$$J(x_n) \leq J(y) \quad \forall y \in K_n(A, r_0) + x_0 .$$

Iterative solver : preconditioned CG method (1/3)

$$Q : N \times N \text{ SPD, } AQ \sim I, QA \sim I$$

Krylov subspace

$$K_n(QA, Qr) := \text{span}[Qr, (QA)Qr, (QA)^2Qr, \dots, (QA)^{n-1}Qr]$$

$x_0 \in \mathbb{R}^N$: initial guess, $r_0 = b - Ax_0$: initial residual

Preconditioned CG method finds $u_n \in K_n(QA, Qr_0)$ satisfying

$$(A(x_0 + u_n), y) = (b, y) \quad \forall y \in K_n(QA, Qr_0)$$

A, Q : SPD \Rightarrow unique solution exists in each Krylov subspace

$$K_n(QA, Qr_0) \quad (1 \leq n \leq M).$$

Iterative solver : preconditioned CG method (2/3)

Algorithm : p-CG method

$$x_0 \in \mathbb{R}^N ,$$

$$r_0 := b - Ax_0 ,$$

$$p_0 := Qr_0 ,$$

do $n = 0, 1, \dots$, until $\|r_n\| / \|r_0\| < \varepsilon$

$$\alpha_n := (Qr_n, r_n) / (Ap_n, p_n) ,$$

$$x_{n+1} := x_n + \alpha_n p_n ,$$

$$r_{n+1} := r_n - \alpha_n Ap_n ,$$

$$\beta_n := (Qr_{n+1}, r_{n+1}) / (Qr_n, r_n) ,$$

$$p_{n+1} := Qr_{n+1} + \beta_n p_n .$$

Q : incomplete LDL^T factorization ignoring fill-in.

Iterative solver : preconditioned CG method (3/3)

Lemma:

for $1 \leq l \leq N_1(Q\mathcal{A}, Qr_0)$

(a) $(r_l, z) = 0 \quad \forall z \in K_l(Q\mathcal{A}, Qr_0),$

(b) $(\mathcal{A}p_l, z) = 0 \quad \forall z \in K_l(Q\mathcal{A}, Qr_0),$

(c) $\text{span}[Qr_0, Qr_1, \dots, Qr_l] = \text{span}[p_0, p_1, \dots, p_l] = K_{l+1}(Q\mathcal{A}, Qr_0).$

proof \leftarrow induction.

Incomplete LDL^T factorization

nonzero column index on k -th row:

$$I(k) = \{\mu \in \{1, 2, \dots, N\}; [A]_{k\mu} \neq 0\}$$

Algorithm: incomplete LDL^T factorization

do $k = 1, 2, \dots, N$

do $i \in I(k)$

$$\lambda_{ki} = a_{ki} - \sum_{j \in I(i) \cap I(k)} l_{ij} \lambda_{kj}$$

$$l_{ki} = \lambda_{ki} / d_{ii}$$

enddo

$$d_{kk} = a_{kk} - \sum_{j \in I(k)} l_{kj} \lambda_{kj}$$

Arnoldi method (1/2)

$A : N \times N$ matrix (general non-singular)

Arnoldi method + finding minimizer on Krylov subspaces

Algorithm : Arnoldi method

$$\|v_1\| = 1$$

do $j = 1, 2, \dots, m$

do $i = 1, 2, \dots, j$

$$h_{ij} := (A v_j, v_i)$$

$$w_j := A v_j - \sum_{1 \leq i \leq j} h_{ij} v_i$$

$$h_{j+1j} := \|w_j\|$$

$$v_{j+1} := w_j / h_{j+1j}.$$

generating orthonormal basis : $\{v_j\}$ in $K_n(A, v_1)$ by Gram-Schmidt method.

Arnoldi method (2/2)

$$[H_m]_{ij} := h_{ij}$$

$$\bar{H}_m := \begin{bmatrix} & H_m \\ 0 \cdots 0 & h_{m+1 m} \end{bmatrix} \in \mathbb{R}^{(m+1) \times m}$$

$$V_m := [v_1, v_2, \dots, v_m], \quad V_{m+1} := [v_1, v_2, \dots, v_m, v_{m+1}].$$

$$V_m^T V_m = I_m,$$

$$A V_m = V_m H_m + w_m e_m^T = V_{m+1} \bar{H}_m,$$

$$V_{m+1}^T A V_m = \bar{H}_m.$$

$$V_{m+1}^T r_0 = \begin{bmatrix} (v_1, r_0) \\ (v_2, r_0) \\ \vdots \\ (v_{m+1}, r_0) \end{bmatrix} = \begin{bmatrix} \beta \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \beta e_1. \quad (\beta = \|r_0\|)$$

GMRES (General Minimum Residual) method

$$r_0 = b - Ax_0$$

Find $u \in K_m(A, r_0)$

$$\|A(u + x_0) - b\| \leq \|A(v + x_0) - b\| \quad \forall v \in K_m(A, r_0).$$

$$u = V_m y, y \in \mathbb{R}^m.$$

$$\begin{aligned} J(y) &:= \|AV_m y - r_0\| \\ &= \|V_{m+1}^T (AV_m y - r_0)\| \\ &= \|(V_{m+1}^T AV_m)y - (V_{m+1}^T r_0)\| \\ &= \|\bar{H}_m y - \beta e_1\|. \quad (\beta = \|r_0\|) \end{aligned}$$

Find $y \in \mathbb{R}^m$

$$J(y) \leq J(z) \quad \forall z \in \mathbb{R}^m.$$

Full Orthogonalization Method (FOM)

$$r_0 = b - Ax_0$$

Find $u \in K_m(A, r_0)$

$$(A(u + x_0) - b, v) = (Au - r_0, v) = 0 \quad \forall v \in K_m(A, r_0).$$

$$u = V_m y, \quad v = V_m z, \quad (y, z \in \mathbb{R}^m).$$

$$\begin{aligned} 0 &= (Au - r_0, v) \\ &= (AV_m y - r_0, V_m z) \\ &= (V_m^T AV_m y - V_m^T r_0, z) \\ &= (H_m y - \beta e_1, z) \end{aligned}$$

Find $y \in \mathbb{R}^m$ s.t. $H_m y = \beta e_1$.

Remark

A : coercive $((Av, v) > 0 \quad \forall v \neq 0) \Rightarrow \exists H_m^{-1}$, otherwise $\Rightarrow ?$

GMRES method (minimization problem)

Given rotation matrices $\Omega_i \in \mathbb{R}^{(m+1) \times (m+1)}$

$$\Omega_i := \begin{bmatrix} I_{i-1} & & & \\ & c_i & s_i & \\ & -s_i & c_i & \\ & & & I_{m-i} \end{bmatrix}, \quad c_i := \frac{h_{11}}{\sqrt{h_{11}^2 + h_{22}^2}}, \quad s_i := \frac{h_{21}}{\sqrt{h_{11}^2 + h_{22}^2}}.$$

$$Q_m := \Omega_m \Omega_{m-1} \cdots \Omega_1 \in \mathbb{R}^{(m+1) \times (m+1)},$$

$$\bar{R}_m := Q_m \bar{H}_m: \text{upper triangular,}$$

$$\bar{g}_m := Q_m(\beta e_1) = [\gamma_1 \ \gamma_2 \ \cdots \ \gamma_{m+1}]^T,$$

$$\bar{R}_m := \begin{bmatrix} R_m \\ 0 \ \cdots \ 0 \end{bmatrix} \quad (R_m \in \mathbb{R}^{m \times m}), \quad \bar{g}_m := \begin{bmatrix} g_m \\ \gamma_{m+1} \end{bmatrix} \quad (g_m \in \mathbb{R}^m).$$

$$\min \| \beta e_1 - \bar{H}_m y \| = \min \| \bar{g}_m - \bar{R}_m y \| = |\gamma_{m+1}| = |s_1 s_2 \cdots s_m| \beta.$$

$y_m = R_m^{-1} g_m$ attains the minimum.

Remark : $\exists R_m^{-1}$ ($1 \leq m \leq M$) for all non-singular matrix A .

FOM (implementation)

FOM method using Givens rotation matrices

$$Q_{m-1} := \Omega_{m-1} \Omega_{m-2} \cdots \Omega_1 \in \mathbb{R}^{m \times m},$$

$$\tilde{R}_m := Q_{m-1} H_m: \text{upper triangular,}$$

$$\tilde{g}_m := Q_{m-1}(\beta e_1) = \bar{g}_{m-1} = [\gamma_1 \ \gamma_2 \ \cdots \ \gamma_m]^T.$$

$$H_m y = \beta e_1$$

$$\Leftrightarrow Q_{m-1} H_m y = Q_{m-1} \beta e_1$$

$$\Leftrightarrow \tilde{R}_m y = \tilde{g}_m.$$

$$H_m : \text{regular} \Leftrightarrow [\tilde{R}_m]_{kk} \neq 0 (1 \leq k \leq m) \Rightarrow y = \tilde{R}_m^{-1} \tilde{g}_m.$$

Relation between GMRES and FOM in case of $\exists y_m^{\text{FOM}}$

$$\rho_m^{\text{GMRES}} := \|b - Ax_m^{\text{GMRES}}\| = |\gamma_{m+1}|, \quad \rho_m^{\text{GMRES}} = |s_m| \rho_{m-1}^{\text{GMRES}}.$$

$$\rho_m^{\text{FOM}} := \|b - Ax_m^{\text{FOM}}\| = \|r_0 - AV_m y_m^{\text{FOM}}\| = h_{m+1 m} |(e_m, y_m^{\text{FOM}})|,$$

$$\rho_m^{\text{FOM}} = h_{m+1 m} \left| \frac{\gamma_m}{h_{m m}^{(m)}} \right| = \frac{h_{m+1 m}}{|h_{m m}^{(m)}|} |\gamma_m| = \frac{|s_m|}{|c_m|} \rho_{m-1}^{\text{GMRES}} = \frac{1}{|c_m|} \rho_m^{\text{GMRES}}.$$

Remark : $x_{m-1}^{\text{GMERS}} = x_m^{\text{GMERS}}$ (stagnation) $\Leftrightarrow H_m$ is singular.

Treatment of essential boundary conditions (1/3)

solution of homogeneous Dirichlet problem:

$$u_h = \sum_{\beta \in \Lambda_Y} [\vec{u}]_{\beta} \varphi_{\beta} \in V_h \Leftrightarrow G\vec{u} = \vec{0}.$$

matrix for the constraint: $G \in \mathbb{R}^{N_D \times N}$, $G^T = [\{ \vec{e}_{\beta} \}_{\beta \in \Lambda_D}]$.

$$\vec{V} := \{ \vec{u} \in \mathbb{R}^N ; G\vec{u} = \vec{0} \}.$$

homogeneous Dirichlet problem:

Find $\vec{u} \in \vec{V}$ such that $(A\vec{u}, \vec{v}) = (\vec{f}, \vec{v}) \quad \forall \vec{v} \in \vec{V}$.

an alternative to solver with re-indexing unknowns:

Lagrange multiplier $\vec{\lambda} \in \mathbb{R}^{N_D}$:

$$\begin{bmatrix} A & G^T \\ G & 0 \end{bmatrix} \begin{bmatrix} \vec{u} \\ \vec{\lambda} \end{bmatrix} = \begin{bmatrix} \vec{f} \\ \vec{0} \end{bmatrix}.$$

matrix size is enlarged to $(N + N_D) \times (N + N_D)$.

$\begin{bmatrix} A & G^T \\ G & 0 \end{bmatrix}$ is regular. \rightarrow factorization with pivoting.

Treatment of essential boundary conditions (2/3)

solution of homogeneous Dirichlet problem:

$$u_h = \sum_{\beta \in \Lambda_Y} [\vec{u}]_{\beta} \varphi_{\beta} \in V_h \Leftrightarrow G\vec{u} = \vec{0}.$$

matrix for the constraint: $G \in \mathbb{R}^{N_D \times N}$, $G^T = [\{ \vec{e}_{\beta} \}_{\beta \in \Lambda_D}]$.

$$\vec{V} := \{ \vec{u} \in \mathbb{R}^N ; G\vec{u} = \vec{0} \}.$$

homogeneous Dirichlet problem:

Find $\vec{u} \in \vec{V}$ such that $(A\vec{u}, \vec{v}) = (\vec{f}, \vec{v}) \quad \forall \vec{v} \in \vec{V}$.

orthogonal projection: $P : \mathbb{R}^N \rightarrow \vec{V}$,

$$P\vec{u} = \vec{u} - \sum_{\beta \in \Lambda_D} (\vec{u}, \vec{e}_{\beta}) \vec{e}_{\beta}.$$

homogeneous Dirichlet problem:

Find $\vec{u} \in \vec{V}$ such that $PAP^T\vec{u} = P\vec{f}$.

preconditioned CG for the linear system with matrix PAP .

Treatment of essential boundary conditions (3/3)

solution of inhomogeneous Dirichlet problem:

$$u_h = \sum_{\beta \in \Lambda_Y} [\vec{u}]_{\beta} \varphi_{\beta} \in V_h(g) \Leftrightarrow G\vec{u} = \vec{g}.$$

inhomogeneous Dirichlet problem:

Find $\vec{u} \in \vec{V}(g)$ such that $(A\vec{u}, \vec{v}) = (\vec{f}, \vec{v}) \quad \forall \vec{v} \in \vec{V}.$

Lagrange multiplier $\vec{\lambda} \in \mathbb{R}^{N_D}$:

$$\begin{bmatrix} A & G^T \\ G & 0 \end{bmatrix} \begin{bmatrix} \vec{u} \\ \vec{\lambda} \end{bmatrix} = \begin{bmatrix} \vec{f} \\ \vec{g} \end{bmatrix}.$$

orthogonal projection: $P : \mathbb{R}^N \rightarrow \vec{V},$

Find $\vec{u}_0 \in \vec{V}$ such that

$$PAP(\vec{u}_0 + \vec{u}_g) = P\vec{f} \Leftrightarrow PAP\vec{u}_0 = P\vec{f} - PAP\vec{u}_g,$$

where \vec{u}_g satisfying $G\vec{u}_g = \vec{g},$ (e.g., $[\vec{u}_g]_{\beta} = 0$ ($\beta \notin \Lambda_D$))

A preconditioned CG method: practical implementation

\mathcal{A}, Q : symmetric, positive on $R(\mathcal{A}) = R(Q)$. $P : \mathbb{R}^N \rightarrow R(\mathcal{A})$.

Algorithm (p-CG with orthogonal projection):

$$x_0 \in R(\mathcal{A}),$$

$$r_0 := P(b - \mathcal{A}x_0),$$

$$p_0 := Qr_0,$$

do $n = 0, 1, \dots$, until $\|r_n\| < \varepsilon$

$$\alpha_n := (Qr_n, r_n) / (\mathcal{A}p_n, p_n),$$

$$x_{n+1} := P(x_n + \alpha_n p_n),$$

$$r_{n+1} := P(r_n - \alpha_n \mathcal{A}p_n),$$

$$\beta_n := (Qr_{n+1}, r_{n+1}) / (Qr_n, r_n),$$

$$p_{n+1} := P(Qr_{n+1} + \beta_n p_n),$$

enddo.

$Q = P\tilde{\mathcal{A}}^{-1}P$, $\tilde{\mathcal{A}}$: an incomplete LDL^T factorization.

References

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