

# On TriMR for solving symmetric quasi-definite linear systems

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# Outline

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- ① Symmetric quasi-definite (SQD) linear systems
- ② The generalized Saunders–Simon–Yip (gSSY) tridiagonalization
- ③ TriMR for SQD linear systems
- ④ Rapoport's method for nonsymmetric positive definite systems
- ⑤ Terminations of the gSSY tridiagonalization
- ⑥ Summary

## Symmetric quasi-definite (SQD) linear systems

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- $M \in \mathbb{R}^{m \times m}$  and  $N \in \mathbb{R}^{n \times n}$  are SPD,  $A \in \mathbb{R}^{m \times n}$  is nonzero,  $b \in \mathbb{R}^m$ , and  $c \in \mathbb{R}^n$ :

$$\begin{bmatrix} M & A \\ A^\top & -N \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} b \\ c \end{bmatrix}.$$

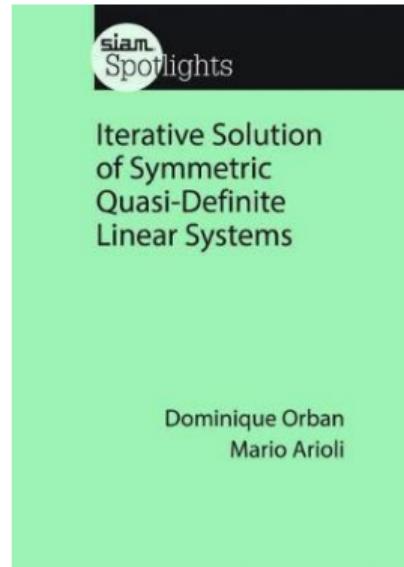
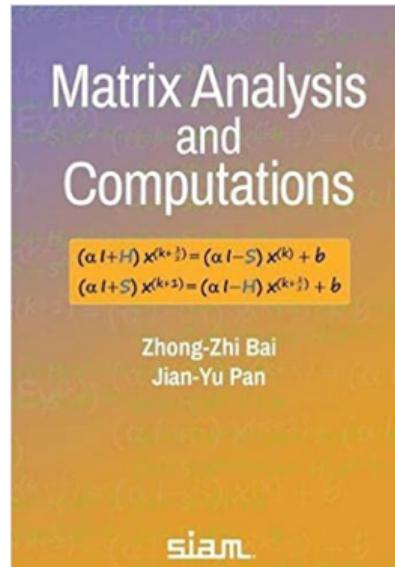
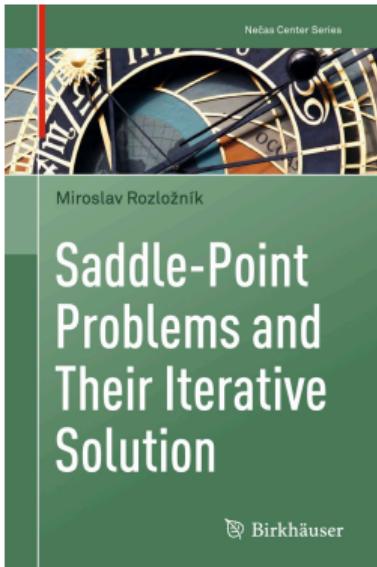
- Computational optimization and computational partial differential equations, etc.
- Symmetric, indefinite, nonsingular
- **Monolithic** methods: solving the system as a whole, for example, SYMMLQ, MINRES

**Segregated** methods: exploiting the block structure, excluding the preconditioning stage, for example, TriCG, TriMR

# Review paper and books

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- Michele Benzi, Gene H. Golub, and Jörg Liesen  
*Numerical solution of saddle point problems.* Acta Numerica (2005).
- Books



# The generalized Saunders–Simon–Yip (gSSY) tridiagonalization

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- The generalized Saunders–Simon–Yip tridiagonalization:

$$\mathbf{A}\mathbf{V}_k = \mathbf{M}\mathbf{U}_{k+1}\mathbf{T}_{k+1,k} = \mathbf{M}\mathbf{U}_k\mathbf{T}_k + \beta_{k+1}\mathbf{M}\mathbf{u}_{k+1}\mathbf{e}_k^\top,$$

$$\mathbf{A}^\top\mathbf{U}_k = \mathbf{N}\mathbf{V}_{k+1}\mathbf{T}_{k,k+1}^\top = \mathbf{N}\mathbf{V}_k\mathbf{T}_k^\top + \gamma_{k+1}\mathbf{N}\mathbf{v}_{k+1}\mathbf{e}_k^\top,$$

$$\mathbf{U}_{k+1}^\top\mathbf{M}\mathbf{U}_{k+1} = \mathbf{V}_{k+1}^\top\mathbf{N}\mathbf{V}_{k+1} = \mathbf{I}_{k+1},$$

where

$$\mathbf{U}_k = [\mathbf{u}_1 \quad \mathbf{u}_2 \quad \cdots \quad \mathbf{u}_k], \quad \mathbf{V}_k = [\mathbf{v}_1 \quad \mathbf{v}_2 \quad \cdots \quad \mathbf{v}_k],$$

and

$$\mathbf{T}_k = \text{tridiag}(\beta_i, \alpha_i, \gamma_{i+1}), \quad \mathbf{T}_{k+1,k} = \begin{bmatrix} \mathbf{T}_k \\ \beta_{k+1}\mathbf{e}_k^\top \end{bmatrix}, \quad \mathbf{T}_{k,k+1} = [\mathbf{T}_k \quad \gamma_{k+1}\mathbf{e}_k].$$

# The generalized Saunders–Simon–Yip tridiagonalization

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## Algorithm 1 Generalized Saunders–Simon–Yip tridiagonalization

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**Require:**  $\mathbf{A} \in \mathbb{R}^{m \times n}$ ,  $\mathbf{b} \in \mathbb{R}^m$  and  $\mathbf{c} \in \mathbb{R}^n$  are nonzero,  $\mathbf{M} \in \mathbb{R}^{m \times m}$  and  $\mathbf{N} \in \mathbb{R}^{n \times n}$  are SPD, subroutines for performing  $\mathbf{M}^{-1}\mathbf{u}$  and  $\mathbf{N}^{-1}\mathbf{v}$

- 1:  $\mathbf{u}_0 = \mathbf{0}$ ,  $\mathbf{v}_0 = \mathbf{0}$ ,  $\beta_1 \mathbf{Mu}_1 = \mathbf{b}$ ,  $\gamma_1 \mathbf{Nv}_1 = \mathbf{c}$ ,
  - 2: **for**  $k = 1, 2, \dots$  **do**
  - 3:      $\mathbf{p} = \mathbf{Av}_k - \gamma_k \mathbf{Mu}_{k-1}$ ,  $\alpha_k = \mathbf{u}_k^\top \mathbf{p}$ ,
  - 4:      $\beta_{k+1} \mathbf{Mu}_{k+1} = \mathbf{p} - \alpha_k \mathbf{Mu}_k$ ,  $\gamma_{k+1} \mathbf{Nv}_{k+1} = \mathbf{A}^\top \mathbf{u}_k - \beta_k \mathbf{Nv}_{k-1} - \alpha_k \mathbf{Nv}_k$ ,
  - 5:     **if**  $\beta_{k+1} = 0$  or  $\gamma_{k+1} = 0$ , **terminate**
  - 6: **end for**
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# TriMR: A minimal residual method for SQD linear systems

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- The  $k$ th TriMR iterate is

$$\begin{bmatrix} \mathbf{x}_k \\ \mathbf{y}_k \end{bmatrix} = \underset{\mathbf{x} \in \text{range}(\mathbf{U}_k), \mathbf{y} \in \text{range}(\mathbf{V}_k)}{\operatorname{argmin}} \left\| \begin{bmatrix} \mathbf{b} \\ \mathbf{c} \end{bmatrix} - \begin{bmatrix} \mathbf{M} & \mathbf{A} \\ \mathbf{A}^\top & -\mathbf{N} \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix} \right\|_{\mathbf{H}^{-1}},$$

where

$$\mathbf{H} = \begin{bmatrix} \mathbf{M} & \mathbf{0} \\ \mathbf{0} & \mathbf{N} \end{bmatrix}.$$

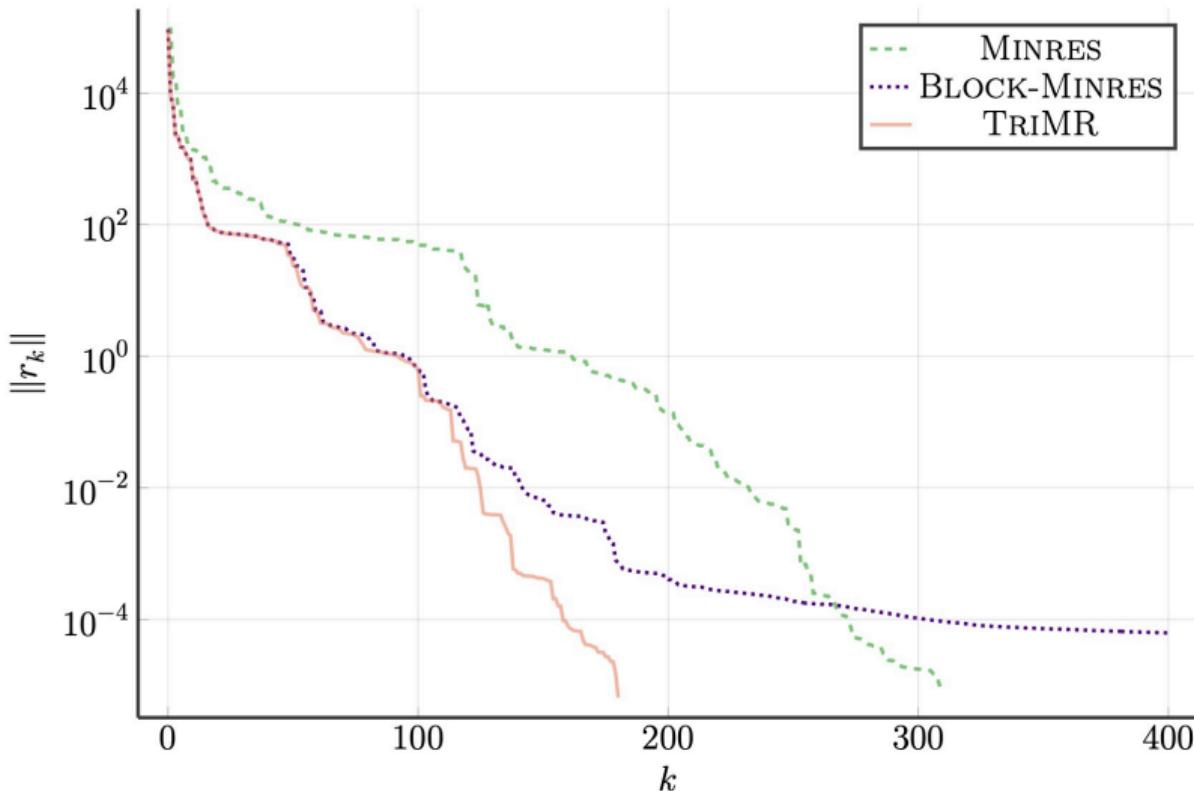
- Equivalent to preconditioned block-MINRES:

$$\begin{bmatrix} \mathbf{M} & \mathbf{A} \\ \mathbf{A}^\top & -\mathbf{N} \end{bmatrix} \begin{bmatrix} \mathbf{x}^1 & \mathbf{x}^2 \\ \mathbf{y}^1 & \mathbf{y}^2 \end{bmatrix} = \begin{bmatrix} \mathbf{b} & \mathbf{0} \\ \mathbf{0} & \mathbf{c} \end{bmatrix}.$$

- Faster than preconditioned MINRES.

## Example: $M = I$ , $N = I$ , $A = \text{lp\_osa\_07}$

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## The subproblem of TriMR

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Let

$$\mathbf{W}_k = \begin{bmatrix} \mathbf{U}_k & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_k \end{bmatrix} \Pi_{2k}, \quad \Pi_{2k} = [\mathbf{e}_1 \ \mathbf{e}_{k+1} \ \cdots \ \mathbf{e}_k \ \mathbf{e}_{2k}],$$

and

$$\mathbf{S}_{k+1,k} = \Pi_{2k+2}^\top \begin{bmatrix} \begin{bmatrix} \mathbf{I}_k \\ \mathbf{0} \end{bmatrix} & \mathbf{T}_{k+1,k} \\ \mathbf{T}_{k,k+1}^\top & -\begin{bmatrix} \mathbf{I}_k \\ \mathbf{0} \end{bmatrix} \end{bmatrix} \Pi_{2k} = \begin{bmatrix} \Theta_1 & \Psi_2 & & & \\ \Psi_2^\top & \Theta_2 & \ddots & & \\ & \ddots & \ddots & \ddots & \Psi_k \\ & & \ddots & \ddots & \Theta_k \\ & & & \ddots & \Psi_{k+1} \end{bmatrix},$$

where

$$\Theta_k = \begin{bmatrix} 1 & \alpha_k \\ \alpha_k & -1 \end{bmatrix} \quad \text{and} \quad \Psi_k = \begin{bmatrix} 0 & \gamma_k \\ \beta_k & 0 \end{bmatrix}.$$

## The subproblem of TriMR

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We have

$$\begin{bmatrix} \mathbf{M} & \mathbf{A} \\ \mathbf{A}^\top & -\mathbf{N} \end{bmatrix} \mathbf{W}_k = \mathbf{H} \mathbf{W}_{k+1} \mathbf{S}_{k+1,k}.$$

Then the  $k$ th TriMR iterate can be determined by

$$\begin{bmatrix} \mathbf{x}_k \\ \mathbf{y}_k \end{bmatrix} = \mathbf{W}_k \mathbf{z}_k$$

where  $\mathbf{z}_k \in \mathbb{R}^{2k}$  solves

$$\min_{\mathbf{z} \in \mathbb{R}^{2k}} \|\mathbf{S}_{k+1,k} \mathbf{z} - (\beta_1 \mathbf{e}_1 + \gamma_1 \mathbf{e}_2)\|.$$

The vector  $\mathbf{z}_k$  can be determined via the QR factorization

$$\mathbf{S}_{k+1,k} = \mathbf{Q}_k \begin{bmatrix} \mathbf{R}_k \\ \mathbf{0} \end{bmatrix},$$

## The subproblem of TriMR

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where

$$\mathbf{Q}_k \in \mathbb{R}^{(2k+2) \times (2k+2)}$$

is a product of reflections, and

$$\mathbf{R}_k = \begin{bmatrix} \delta_1 & \sigma_1 & \eta_1 & \lambda_1 & \mu_1 \\ & \ddots & \ddots & \ddots & \ddots \\ & & \ddots & \ddots & \ddots \\ & & & \ddots & \mu_{2k-4} \\ & & & & \lambda_{2k-3} \\ & & & & \eta_{2k-2} \\ & & & & \sigma_{2k-1} \\ & & & & \delta_{2k} \end{bmatrix} \in \mathbb{R}^{(2k) \times (2k)}.$$

## The subproblem of TriMR

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Theorem ( $\mathbf{R}_k$  has only three nonzero diagonals)

*The upper triangular matrix  $\mathbf{R}_k$  of the QR factorization has the following form:*

$$\mathbf{R}_k = \begin{bmatrix} \delta_1 & 0 & \eta_1 & 0 & \mu_1 & & \\ & \ddots & \ddots & \ddots & \ddots & \ddots & \\ & & \ddots & \ddots & \ddots & \ddots & \mu_{2k-4} \\ & & & \ddots & \ddots & \ddots & 0 \\ & & & & \ddots & \ddots & \eta_{2k-2} \\ & & & & & \ddots & 0 \\ & & & & & & \delta_{2k} \end{bmatrix}.$$

## Rapoport's method for nonsymmetric positive definite systems

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- The equivalent nonsymmetric positive definite system

$$\begin{bmatrix} M & A \\ -A^T & N \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} b \\ -c \end{bmatrix}, \quad H = \begin{bmatrix} M & A \\ -A^T & N \end{bmatrix}, \quad S = \begin{bmatrix} & A \\ -A^T & \end{bmatrix}.$$

- The  $k$ th Rapoport iterate is

$$\begin{bmatrix} x_k \\ y_k \end{bmatrix} = \underset{\mathbf{z} \in \mathcal{K}_k}{\operatorname{argmin}} \left\| \begin{bmatrix} b \\ -c \end{bmatrix} - \begin{bmatrix} M & A \\ -A^T & N \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \right\|_{H^{-1}},$$

where the Krylov subspace

$$\mathcal{K}_k = \operatorname{span} \left\{ H^{-1} \begin{bmatrix} b \\ -c \end{bmatrix}, H^{-1}S \begin{bmatrix} b \\ -c \end{bmatrix}, \dots, (H^{-1}S)^{k-1} \begin{bmatrix} b \\ -c \end{bmatrix} \right\}.$$

- The skew-symmetric Lanczos:  $SQ_k = HQ_{k+1}T_{k+1,k}$ .

## TriMR is faster than Rapoport's method

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- The  $k$ th TriMR iterate is

$$\begin{bmatrix} \mathbf{x}_k \\ \mathbf{y}_k \end{bmatrix} = \underset{\mathbf{x} \in \text{range}(\mathbf{U}_k), \mathbf{y} \in \text{range}(\mathbf{V}_k)}{\operatorname{argmin}} \left\| \begin{bmatrix} \mathbf{b} \\ \mathbf{c} \end{bmatrix} - \begin{bmatrix} \mathbf{M} & \mathbf{A} \\ \mathbf{A}^\top & -\mathbf{N} \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix} \right\|_{\mathbf{H}^{-1}}.$$

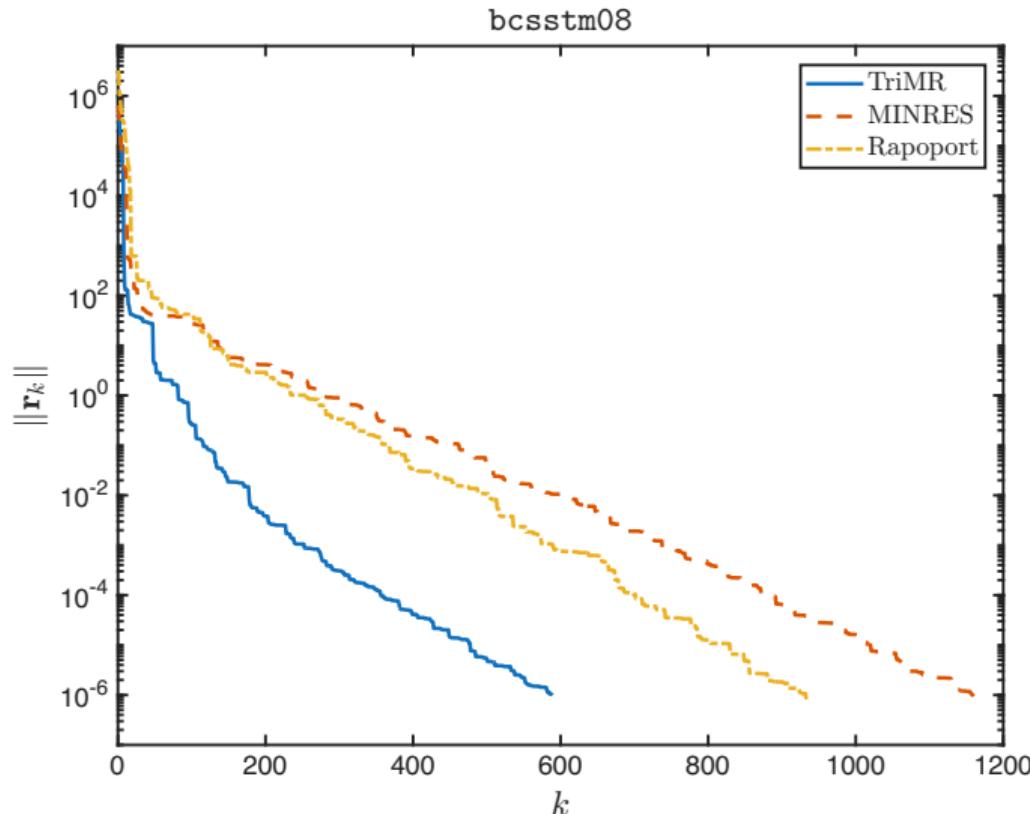
- The  $k$ th Rapoport iterate is

$$\begin{aligned} \begin{bmatrix} \mathbf{x}_k \\ \mathbf{y}_k \end{bmatrix} &= \underset{\mathbf{z} \in \mathcal{K}_k}{\operatorname{argmin}} \left\| \begin{bmatrix} \mathbf{b} \\ -\mathbf{c} \end{bmatrix} - \begin{bmatrix} \mathbf{M} & \mathbf{A} \\ -\mathbf{A}^\top & \mathbf{N} \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix} \right\|_{\mathbf{H}^{-1}} \\ &= \underset{\mathbf{z} \in \mathcal{K}_k}{\operatorname{argmin}} \left\| \begin{bmatrix} \mathbf{b} \\ \mathbf{c} \end{bmatrix} - \begin{bmatrix} \mathbf{M} & \mathbf{A} \\ \mathbf{A}^\top & -\mathbf{N} \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix} \right\|_{\mathbf{H}^{-1}}. \end{aligned}$$

- TriMR is faster than Rapoport's method since  $\mathcal{K}_k \subset \text{range} \left( \begin{bmatrix} \mathbf{U}_k & \\ & \mathbf{V}_k \end{bmatrix} \right)$ .

## Example: $M = I$ , $N = I$ , $A = bcsstm08$

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# Terminations of gSSY

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## Algorithm 1 Generalized Saunders–Simon–Yip tridiagonalization

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**Require:**  $\mathbf{A} \in \mathbb{R}^{m \times n}$ ,  $\mathbf{b} \in \mathbb{R}^m$  and  $\mathbf{c} \in \mathbb{R}^n$  are nonzero,  $\mathbf{M} \in \mathbb{R}^{m \times m}$  and  $\mathbf{N} \in \mathbb{R}^{n \times n}$  are SPD, subroutines for performing  $\mathbf{M}^{-1}\mathbf{u}$  and  $\mathbf{N}^{-1}\mathbf{v}$

- 1:  $\mathbf{u}_0 = \mathbf{0}$ ,  $\mathbf{v}_0 = \mathbf{0}$ ,  $\beta_1 \mathbf{M}\mathbf{u}_1 = \mathbf{b}$ ,  $\gamma_1 \mathbf{N}\mathbf{v}_1 = \mathbf{c}$ ,
  - 2: **for**  $k = 1, 2, \dots$  **do**
  - 3:      $\mathbf{p} = \mathbf{A}\mathbf{v}_k - \gamma_k \mathbf{M}\mathbf{u}_{k-1}$ ,  $\alpha_k = \mathbf{u}_k^\top \mathbf{p}$ ,
  - 4:      $\beta_{k+1} \mathbf{M}\mathbf{u}_{k+1} = \mathbf{p} - \alpha_k \mathbf{M}\mathbf{u}_k$ ,  $\gamma_{k+1} \mathbf{N}\mathbf{v}_{k+1} = \mathbf{A}^\top \mathbf{u}_k - \beta_k \mathbf{N}\mathbf{v}_{k-1} - \alpha_k \mathbf{N}\mathbf{v}_k$ ,
  - 5:     **if**  $\beta_{k+1} = 0$  or  $\gamma_{k+1} = 0$ , **terminate**
  - 6: **end for**
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- gSSY must terminate in  $\ell \leq \min(m, n)$  steps in exact arithmetic, and either  $\beta_{\ell+1} = 0$  or  $\beta_{\ell+1} \neq 0$  and  $\gamma_{\ell+1} = 0$ .  $\beta_{\ell+1} = \gamma_{\ell+1} = 0$  ensures a lucky termination (i.e., the exact solution is in the final subspace generated by gSSY). When  $\beta_{\ell+1}$  and  $\gamma_{\ell+1}$  are not simultaneous zero, unlucky terminations.

## Unlucky terminations of gSSY: case I

Example (The case that  $\beta_{\ell+1} = 0$  and  $\gamma_{\ell+1} \neq 0$ )

The solution to the SQD linear system with

$$\mathbf{M} = \mathbf{N} = \mathbf{I}_3, \quad \mathbf{A} = \begin{bmatrix} -1 & 2 & 0 \\ 1 & -1 & 1 \\ 0 & 0 & -1 \end{bmatrix}, \quad \mathbf{b} = \mathbf{c} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix},$$

is  $[1 \ 2 \ 1 \ -3 \ 0 \ 1]^\top / 4$ . gSSY terminates at step  $\ell = 2$  with  $\beta_{\ell+1} = 0$ , and we have  $\gamma_{\ell+1} = 1 \neq 0$  and  $\mathbf{U}_\ell = \mathbf{V}_\ell = [\mathbf{e}_1 \ \mathbf{e}_2]$ . Obviously,

$$[1 \ 2 \ 1 \ -3 \ 0 \ 1]^\top \notin \text{range} \left( \begin{bmatrix} \mathbf{U}_\ell & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_\ell \end{bmatrix} \right).$$

## Unlucky terminations of gSSY: case II

Example (The case that  $\beta_{\ell+1} \neq 0$  and  $\gamma_{\ell+1} = 0$ )

The solution to the SQD linear system with

$$\mathbf{M} = \mathbf{N} = \mathbf{I}_3, \quad \mathbf{A} = \begin{bmatrix} -1 & 1 & 0 \\ 3 & -1 & 0 \\ 0 & 1 & -1 \end{bmatrix}, \quad \mathbf{b} = \mathbf{c} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix},$$

is  $[11 \ 8 \ -1 \ -2 \ 2 \ 1]^\top / 15$ . gSSY terminates at step  $\ell = 2$  with  $\beta_{\ell+1} = 1 \neq 0$  and  $\gamma_{\ell+1} = 0$ , and we have  $\mathbf{U}_{\ell+1} = \mathbf{I}_3$ ,  $\mathbf{V}_\ell = [\mathbf{e}_1 \ \mathbf{e}_2]$ . Obviously,

$$[11 \ 8 \ -1 \ -2 \ 2 \ 1]^\top \notin \text{range} \left( \begin{bmatrix} \mathbf{U}_{\ell+1} & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_\ell \end{bmatrix} \right).$$

# Improved generalized SSY tridiagonalization

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**Algorithm 2** Improved generalized Saunders–Simon–Yip tridiagonalization: igSSY( $\mathbf{M}, \mathbf{N}, \mathbf{A}, \mathbf{b}, \mathbf{c}$ )

**Require:**  $\mathbf{A} \in \mathbb{R}^{m \times n}$ ,  $\mathbf{b} \in \mathbb{R}^m$  and  $\mathbf{c} \in \mathbb{R}^n$  are not simultaneously zero,  $\mathbf{M} \in \mathbb{R}^{m \times m}$  and  $\mathbf{N} \in \mathbb{R}^{n \times n}$  are SPD, subroutines for performing  $\mathbf{M}^{-1}\mathbf{u}$  and  $\mathbf{N}^{-1}\mathbf{v}$

```
1:  $\mathbf{u}_0 = \mathbf{0}, \mathbf{v}_0 = \mathbf{0}$ 
2:  $\mathbf{u} = \mathbf{M}^{-1}\mathbf{b}, \beta_1 = \sqrt{\mathbf{b}^\top \mathbf{u}}$ ; if  $\beta_1 \neq 0$ , then  $\mathbf{u}_1 = \mathbf{u}/\beta_1$  end if
3:  $\mathbf{v} = \mathbf{N}^{-1}\mathbf{c}, \gamma_1 = \sqrt{\mathbf{c}^\top \mathbf{v}}$ ; if  $\gamma_1 \neq 0$ , then  $\mathbf{v}_1 = \mathbf{v}/\gamma_1$  end if
4:  $k = 1$ 
5: while  $\beta_k \gamma_k \neq 0$  do
6:    $\mathbf{p} = \mathbf{A}\mathbf{v}_k - \gamma_k \mathbf{M}\mathbf{u}_{k-1}$ 
7:    $\alpha_k = \mathbf{u}_k^\top \mathbf{p}, \mathbf{p} = \mathbf{p} - \alpha_k \mathbf{M}\mathbf{u}_k$ 
8:    $\mathbf{u} = \mathbf{M}^{-1}\mathbf{p}, \beta_{k+1} = \sqrt{\mathbf{p}^\top \mathbf{u}}$ ; if  $\beta_{k+1} \neq 0$ , then  $\mathbf{u}_{k+1} = \mathbf{u}/\beta_{k+1}$  end if
9:    $\mathbf{q} = \mathbf{A}^\top \mathbf{u}_k - \beta_k \mathbf{N}\mathbf{v}_{k-1} - \alpha_k \mathbf{N}\mathbf{v}_k$ 
10:   $\mathbf{v} = \mathbf{N}^{-1}\mathbf{q}, \gamma_{k+1} = \sqrt{\mathbf{q}^\top \mathbf{v}}$ ; if  $\gamma_{k+1} \neq 0$ , then  $\mathbf{v}_{k+1} = \mathbf{v}/\gamma_{k+1}$  end if
11:   $k = k + 1$ 
12: end while
13:  $\ell = k - 1$ 
14: if  $\beta_{\ell+1} = 0$  and  $\gamma_{\ell+1} = 0$ , terminate
15: if  $\beta_{\ell+1} = 0$  then
16:   for  $k = \ell + 1, \ell + 2, \dots$  do
17:      $\alpha_k \mathbf{M}\mathbf{u}_k = \mathbf{A}\mathbf{v}_k - \gamma_k \mathbf{M}\mathbf{u}_{k-1}$ 
18:      $\gamma_{k+1} \mathbf{N}\mathbf{v}_{k+1} = \mathbf{A}^\top \mathbf{u}_k - \alpha_k \mathbf{N}\mathbf{v}_k$ 
19:     if  $\alpha_k = 0$  or  $\gamma_{k+1} = 0$ , terminate
20:   end for
21: else if  $\gamma_{\ell+1} = 0$  then
22:   for  $k = \ell + 1, \ell + 2, \dots$  do
23:      $\alpha_k \mathbf{N}\mathbf{v}_k = \mathbf{A}^\top \mathbf{u}_k - \beta_k \mathbf{N}\mathbf{v}_{k-1}$ 
24:      $\beta_{k+1} \mathbf{M}\mathbf{u}_{k+1} = \mathbf{A}\mathbf{v}_k - \alpha_k \mathbf{M}\mathbf{u}_k$ 
25:     if  $\alpha_k = 0$  or  $\beta_{k+1} = 0$ , terminate
26:   end for
27: end if
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## Terminations of igSSY

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- Assume that gSSY terminates at step  $\ell$ , i.e.,  $\beta_{\ell+1} = 0$  or  $\gamma_{\ell+1} = 0$ .
- Assume that igSSY terminates at step  $L \geq \ell$ . Five cases occur (see lines 14, 19, and 25): for  $k = \ell, \dots, L$ ,

**Case I:**  $\beta_{\ell+1} = \gamma_{\ell+1} = 0$ ;

**Case II:**  $\alpha_{L+1} = 0, \beta_{k+1} = 0, \gamma_{k+1} \neq 0$ ;

**Case III:**  $\alpha_{L+1} \neq 0, \beta_{k+1} = 0, \gamma_{k+1} \neq 0, \gamma_{L+2} = 0$ ;

**Case IV:**  $\alpha_{L+1} = 0, \beta_{k+1} \neq 0, \gamma_{k+1} = 0$ ;

**Case V:**  $\alpha_{L+1} \neq 0, \beta_{k+1} \neq 0, \gamma_{k+1} = 0, \beta_{L+2} = 0$ .

All are lucky terminations. The solution of the SQD linear system belongs to the final subspace generated by igSSY.

# Elliptic singular value decomposition (ESVD)

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- Given SPD  $\mathbf{M}$  and  $\mathbf{N}$ , ESVD of  $\mathbf{A}$  is

$$\mathbf{A} = \mathbf{MP}\Sigma\mathbf{Q}^\top\mathbf{N},$$

where  $\Sigma = \text{diag}(\sigma_1, \dots, \sigma_p)$ ,  $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_p \geq 0$ ,  $p = \min(m, n)$ , and  $\mathbf{P}$  and  $\mathbf{Q}$  satisfy

$$\mathbf{P}^\top\mathbf{MP} = \mathbf{I}_m, \quad \mathbf{Q}^\top\mathbf{NQ} = \mathbf{I}_n.$$

## Theorem

Assume that *igSSY* terminates at step  $L$ . If  $d$  is the number of distinct elliptic singular values of  $\mathbf{A}$  and  $r$  is the rank of  $\mathbf{A}$ , then we have  $L \leq \min(2d, r)$ .

## Summary

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- We proved that the upper triangular factor of the QR factorization used in TriMR only has three nonzero diagonals, and based on this fact we provided simplified short recurrences for TriMR, which reduce the work per iteration.
- We proved that the TriMR method for SQD linear systems is faster than Rapoport's method for the equivalent nonsymmetric positive definite linear systems.
- We proposed igSSY, which avoids unlucky terminations of gSSY. Improved TriMR can be defined in the same fashion as TriMR, but is based on igSSY instead of gSSY.
- Algorithms that fully leverage the underlying structure of a problem can be significantly more efficient than general-purpose algorithms!

## The related work

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- Kui Du, Jia-Jun Fan, Xiao-Hui Sun, Fang Wang, and Ya-Lan Zhang  
On Krylov subspace methods for skew-symmetric and shifted skew-symmetric linear systems  
Advances in Computational Mathematics (2024) 50:78
- Kui Du, Jia-Jun Fan, and Ya-Lan Zhang  
Improved TriCG and TriMR methods for symmetric quasi-definite linear systems  
Numerical Linear Algebra with Applications, 2025, 32:e70026

**Thanks!**