

RSMAR: An iterative method for range-symmetric linear systems

Kui Du

kuidu@xmu.edu.cn

School of Mathematical Sciences, Xiamen University

<https://kuidu.github.io>

joint work with Jia-Jun Fan and Fang Wang

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Two main references

- A. Montoison, D. Orban, and M. A. Saunders.
MINARES: An iterative solver for symmetric linear systems.
arXiv:2310.01757, 2023.
- Y. Liu, A. Milzarek, and F. Roosta.
Obtaining pseudo-inverse solutions with MINRES.
arXiv:2309.17096, 2023.

Outline

- ① The pseudoinverse solution of range-symmetric systems
- ② GMRES-type methods for singular range-symmetric systems
- ③ MINARES for symmetric systems
- ④ Numerical experiments
- ⑤ Summary

The pseudoinverse solution

- $\mathbf{Ax} = \mathbf{b}$, $\mathbf{A} \in \mathbb{R}^{m \times n}$, $\mathbf{b} \in \mathbb{R}^m$.

Consistent if $\mathbf{b} \in \text{range}(\mathbf{A})$, otherwise, inconsistent.

- \mathbf{A}^\dagger : the Moore–Penrose inverse of \mathbf{A}
- $\mathbf{A}^\dagger \mathbf{b}$: the pseudoinverse solution

| $\mathbf{Ax} = \mathbf{b}$ | $\text{rank}(\mathbf{A})$ | $\mathbf{A}^\dagger \mathbf{b}$ |
|----------------------------|---------------------------|------------------------------------|
| consistent | $= n$ | unique solution |
| consistent | $< n$ | unique minimum 2-norm solution |
| inconsistent | $= n$ | unique least-squares (LS) solution |
| inconsistent | $< n$ | unique minimum 2-norm LS solution |

Range-symmetric systems

- range-symmetric \mathbf{A} : $\text{range}(\mathbf{A}) = \text{range}(\mathbf{A}^\top)$.

Fact I:

$$\mathbf{A} = \mathbf{U} \begin{bmatrix} \mathbf{C} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \mathbf{U}^\top.$$

(\mathbf{C} is invertible and \mathbf{U} is orthogonal.)

Fact II:

$$\mathbf{A}^\dagger = \mathbf{A}^D = \mathbf{U} \begin{bmatrix} \mathbf{C}^{-1} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \mathbf{U}^\top. \quad (\text{Drazin inverse})$$

Fact III:

$$\begin{aligned} \mathbf{A}^\dagger \mathbf{b} + \text{null}(\mathbf{A}) &= \{\mathbf{x} \in \mathbb{R}^n : \mathbf{A}^\top \mathbf{A} \mathbf{x} = \mathbf{A}^\top \mathbf{b}\} \\ &= \{\mathbf{x} \in \mathbb{R}^n : \mathbf{A}^2 \mathbf{x} = \mathbf{A} \mathbf{b}\}. \end{aligned}$$

Krylov subspaces and (least squares) solutions

- $\mathbf{x}_0 \in \mathbb{R}^n$, $\mathbf{r}_0 := \mathbf{b} - \mathbf{A}\mathbf{x}_0$,

$$\mathcal{K}_k(\mathbf{A}, \mathbf{r}_0) := \text{span}\{\mathbf{r}_0, \mathbf{A}\mathbf{r}_0, \dots, \mathbf{A}^{k-1}\mathbf{r}_0\}.$$

- ℓ : the **grade** of \mathbf{r}_0 with respect to \mathbf{A} , i.e., ℓ satisfies

$$\dim \mathcal{K}_k(\mathbf{A}, \mathbf{r}_0) = \begin{cases} k, & \text{if } k \leq \ell, \\ \ell, & \text{if } k \geq \ell + 1. \end{cases}$$

- For any $\mathbf{A} \in \mathbb{R}^{n \times n}$,
 - (i) $\mathbf{b} \notin \text{range}(\mathbf{A})$: # LS solution in $\mathbf{x}_0 + \mathcal{K}_{\ell-1}(\mathbf{A}, \mathbf{r}_0) \leq 1$;
 - (ii) $\mathbf{b} \in \text{range}(\mathbf{A})$: # solution in $\mathbf{x}_0 + \mathcal{K}_{\ell}(\mathbf{A}, \mathbf{r}_0) \leq 1$.

GMRES for singular range-symmetric systems

- GMRES: $\mathbf{x}_k := \operatorname{argmin}_{\mathbf{x} \in \mathbf{x}_0 + \mathcal{K}_k(\mathbf{A}, \mathbf{r}_0)} \|\mathbf{b} - \mathbf{A}\mathbf{x}\|.$
- For singular range-symmetric \mathbf{A} [BW97]:
 - (i) $\mathbf{b} \in \operatorname{range}(\mathbf{A})$: $\mathbf{x}_\ell = \text{solution}$. More precisely,

$$\mathbf{x}_\ell = \mathbf{A}^\dagger \mathbf{b} + (\mathbf{I} - \mathbf{A}^\dagger \mathbf{A}) \mathbf{x}_0,$$

the orthogonal projection of \mathbf{x}_0 onto the solution set

$$\{\mathbf{x} \in \mathbb{R}^n : \mathbf{A}\mathbf{x} = \mathbf{b}\} = \mathbf{A}^\dagger \mathbf{b} + \operatorname{null}(\mathbf{A}).$$

- (ii) $\mathbf{b} \notin \operatorname{range}(\mathbf{A})$: $\mathbf{x}_{\ell-1} = \text{LS solution}$. Which one?

[BW97] P. N. Brown and H. F. Walker. *GMRES on (nearly) singular systems*. SIMAX, 1997.

A lifting strategy [LMR23]

- If $\text{range}(\mathbf{A}) = \text{range}(\mathbf{A}^\top)$ and $\mathbf{b} \notin \text{range}(\mathbf{A})$, then the lifted vector,

$$\tilde{\mathbf{x}}_{\ell-1} := \mathbf{x}_{\ell-1} - \frac{\mathbf{r}_{\ell-1}^\top (\mathbf{x}_{\ell-1} - \mathbf{x}_0)}{\mathbf{r}_{\ell-1}^\top \mathbf{r}_{\ell-1}} \mathbf{r}_{\ell-1},$$

is the **orthogonal projection** of \mathbf{x}_0 onto the least squares solution set $\{\mathbf{x} \in \mathbb{R}^n : \mathbf{A}^\top \mathbf{A} \mathbf{x} = \mathbf{A}^\top \mathbf{b}\}$, i.e.,

$$\tilde{\mathbf{x}}_{\ell-1} = \mathbf{A}^\dagger \mathbf{b} + (\mathbf{I} - \mathbf{A}^\dagger \mathbf{A}) \mathbf{x}_0.$$

- $\mathbf{x}_0 = \mathbf{0} \Rightarrow \tilde{\mathbf{x}}_{\ell-1} = \mathbf{A}^\dagger \mathbf{b}.$

[LMR23] Y. Liu, A. Milzarek, and F. Roosta. *Obtaining pseudo-inverse solutions with MINRES*. arXiv:2309.17096, 2023.

GMRES for singular (skew-)symmetric systems

- “(skew-)symmetric” \in “range-symmetric”
- For symmetric \mathbf{A} , if $\mathbf{b} \notin \text{range}(\mathbf{A})$, then $\mathbf{x}_{\ell-1}$ = LS solution, but not necessarily $\mathbf{A}^\dagger \mathbf{b}$ [CPS11].

Trigger the lifting strategy if required.

- For skew-symmetric \mathbf{A} , i.e., $\mathbf{A}^\top = -\mathbf{A}$, if $\mathbf{b} \notin \text{range}(\mathbf{A})$, then

$$\mathbf{r}_{\ell-1}^\top (\mathbf{x}_{\ell-1} - \mathbf{x}_0) = 0,$$

which implies

$$\mathbf{x}_{\ell-1} = \tilde{\mathbf{x}}_{\ell-1}.$$

[CPS11] S.-C. T. Choi, C. C. Paige, and M. A. Saunders. *MINRES-QLP: A Krylov subspace method for indefinite or singular symmetric systems*. SISC, 2011.

Summary of GMRES-type methods

- Let \mathbf{A} be range-symmetric. For simplicity, we set $\mathbf{x}_0 = \mathbf{0}$.

| Method | Minimization property at step k |
|---------|---|
| GMRES | $\mathbf{x}_k := \operatorname{argmin}_{\mathbf{x} \in \mathcal{K}_k(\mathbf{A}, \mathbf{b})} \ \mathbf{b} - \mathbf{Ax}\ $ |
| RRGMRES | $\mathbf{x}_k^{\mathbf{R}} := \operatorname{argmin}_{\mathbf{x} \in \mathcal{K}_k(\mathbf{A}, \mathbf{Ab})} \ \mathbf{b} - \mathbf{Ax}\ $ |
| DGMRES | $\mathbf{x}_k^{\mathbf{D}} := \operatorname{argmin}_{\mathbf{x} \in \mathcal{K}_k(\mathbf{A}, \mathbf{Ab})} \ \mathbf{A}(\mathbf{b} - \mathbf{Ax})\ $ |
| RSMAR | $\mathbf{x}_k^{\mathbf{A}} := \operatorname{argmin}_{\mathbf{x} \in \mathcal{K}_k(\mathbf{A}, \mathbf{b})} \ \mathbf{A}(\mathbf{b} - \mathbf{Ax})\ $ |

Consistent: $\mathbf{x}_\ell = \mathbf{x}_\ell^{\mathbf{R}} = \mathbf{x}_\ell^{\mathbf{D}} = \mathbf{A}^\dagger \mathbf{b}$, $\mathbf{x}_\ell^{\mathbf{A}} = ???$

Inconsistent: $\tilde{\mathbf{x}}_{\ell-1} = \mathbf{x}_{\ell-1}^{\mathbf{R}} = \mathbf{x}_{\ell-1}^{\mathbf{D}} = \mathbf{A}^\dagger \mathbf{b}$, $\mathbf{x}_{\ell-1}^{\mathbf{A}} = ???$

[MOS23] A. Montoison, D. Orban, and M. A. Saunders. *MINARES: An iterative solver for symmetric linear systems*. arXiv:2310.01757, 2023.

RSMAR for range-symmetric systems

- RSMAR: $\mathbf{x}_k^A := \operatorname{argmin}_{\mathbf{x} \in \mathcal{K}_k(\mathbf{A}, \mathbf{b})} \|\mathbf{A}(\mathbf{b} - \mathbf{A}\mathbf{x})\|$, (well-defined?)
- For range-symmetric \mathbf{A} , if $\mathbf{b} \in \operatorname{range}(\mathbf{A})$, then $\mathbf{x}_\ell^A = \mathbf{x}_\ell$, and if $\mathbf{b} \notin \operatorname{range}(\mathbf{A})$, then $\mathbf{x}_{\ell-1}^A = \mathbf{x}_{\ell-1}$. In other words, the final iterates of GMRES and RSMAR are the same.
- For inconsistent systems, $\|\mathbf{r}_{\ell-1}\| \neq 0$, but $\|\mathbf{A}\mathbf{r}_{\ell-1}\| = 0$.
- RSMAR for $\mathbf{A}\mathbf{x} = \mathbf{b}$ “=” GMRES for $\mathbf{A}\mathbf{y} = \mathbf{A}\mathbf{b}$, $\mathbf{y} = \mathbf{A}\mathbf{x}$:

$$\min_{\mathbf{x} \in \mathcal{K}_k(\mathbf{A}, \mathbf{b})} \|\mathbf{A}(\mathbf{b} - \mathbf{A}\mathbf{x})\| = \min_{\mathbf{y} \in \mathcal{K}_k(\mathbf{A}, \mathbf{A}\mathbf{b})} \|\mathbf{A}\mathbf{b} - \mathbf{A}\mathbf{y}\|.$$

Implementation I (inspired by simpler GMRES)

- Arnoldi process yields $\text{span}\{\hat{\mathbf{v}}_1, \hat{\mathbf{v}}_2, \dots, \hat{\mathbf{v}}_k\} = \mathcal{K}_k(\mathbf{A}, \mathbf{Ab})$,

$$\hat{\beta}_1 \hat{\mathbf{v}}_1 = \mathbf{Ab}, \quad \mathbf{A} \hat{\mathbf{V}}_k = \hat{\mathbf{V}}_{k+1} \hat{\mathbf{H}}_{k+1,k}, \quad \hat{\mathbf{V}}_k^\top \hat{\mathbf{V}}_k = \mathbf{I}_k.$$

- $\min_{\mathbf{y} \in \mathcal{K}_k(\mathbf{A}, \mathbf{Ab})} \|\mathbf{Ab} - \mathbf{Ay}\| = \min_{\hat{\mathbf{z}} \in \mathbb{R}^k} \|\hat{\beta}_1 \mathbf{e}_1 - \hat{\mathbf{H}}_{k+1,k} \hat{\mathbf{z}}\| \Rightarrow$

$$\mathbf{y}_k = \hat{\mathbf{V}}_k \hat{\mathbf{z}}_k \text{ with } \hat{\mathbf{z}}_k = \underset{\hat{\mathbf{z}} \in \mathbb{R}^k}{\text{argmin}} \|\hat{\beta}_1 \mathbf{e}_1 - \hat{\mathbf{H}}_{k+1,k} \hat{\mathbf{z}}\|.$$

- $\mathcal{K}_k(\mathbf{A}, \mathbf{b}) = \text{span}\{\mathbf{b}, \hat{\mathbf{v}}_1, \dots, \hat{\mathbf{v}}_{k-1}\}$ and $\mathbf{y}_k = \mathbf{Ax}_k^A \Rightarrow$

$$\mathbf{x}_k^A = \begin{bmatrix} \mathbf{b} & \hat{\mathbf{V}}_{k-1} \end{bmatrix} \mathbf{z}_k,$$

where \mathbf{z}_k solves

$$\mathbf{A} \begin{bmatrix} \mathbf{b} & \hat{\mathbf{V}}_{k-1} \end{bmatrix} \mathbf{z} = \hat{\mathbf{V}}_k \begin{bmatrix} \hat{\beta}_1 \mathbf{e}_1 & \hat{\mathbf{H}}_{k,k-1} \end{bmatrix} \mathbf{z} = \hat{\mathbf{V}}_k \hat{\mathbf{z}}_k.$$

Implementation II (inspired by RRGMR)

- Arnoldi process yields $\text{span}\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\} = \mathcal{K}_k(\mathbf{A}, \mathbf{b})$,

$$\beta_1 \mathbf{v}_1 = \mathbf{b}, \quad \mathbf{A}\mathbf{V}_k = \mathbf{V}_{k+1}\mathbf{H}_{k+1,k}, \quad \mathbf{V}_k^\top \mathbf{V}_k = \mathbf{I}_k.$$

- The subproblem:

$$\begin{aligned} \min_{\mathbf{x} \in \mathcal{K}_k(\mathbf{A}, \mathbf{b})} \|\mathbf{A}(\mathbf{b} - \mathbf{A}\mathbf{x})\| \\ = \min_{\mathbf{z} \in \mathbb{R}^k} \|\beta_1 \mathbf{H}_{k+2,k+1} \mathbf{e}_1 - \mathbf{H}_{k+2,k+1} \mathbf{H}_{k+1,k} \mathbf{z}\|. \end{aligned}$$

- Two QR factorizations are required:

$$\mathbf{H}_{k+1,k} = \mathbf{Q}_{k+1} \begin{bmatrix} \mathbf{R}_k \\ \mathbf{0} \end{bmatrix}, \quad \mathbf{H}_{k+2,k+1} \mathbf{Q}_{k+1} \begin{bmatrix} \mathbf{I}_k \\ \mathbf{0} \end{bmatrix} = \tilde{\mathbf{Q}}_{k+2} \begin{bmatrix} \tilde{\mathbf{R}}_k \\ \mathbf{0} \end{bmatrix}.$$

- $\mathbf{x}_k^A = \mathbf{V}_k \mathbf{R}_k^{-1} \tilde{\mathbf{R}}_k^{-1} \begin{bmatrix} \mathbf{I}_k & \mathbf{0} \end{bmatrix} \tilde{\mathbf{Q}}_{k+2}^\top \beta_1 (h_{11} \mathbf{e}_1 + h_{21} \mathbf{e}_2).$

MINARES for symmetric systems [MOS23]

- GMRES for symmetric systems “ \Leftrightarrow ” MINRES
- RSMAR for symmetric systems “ \Leftrightarrow ” MINARES
- The MINARES implementation in [MOS23] is based on the Arnoldi relation $\mathbf{A}\mathbf{V}_k = \mathbf{V}_{k+1}\mathbf{H}_{k+1,k}$, and thus can be viewed as a short recurrence variant of RSMAR-II.
- We derive a new implementation for MINARES, which is based on $\mathbf{A}\hat{\mathbf{V}}_k = \hat{\mathbf{V}}_{k+1}\hat{\mathbf{H}}_{k+1,k}$ and can be viewed as a short recurrence variant of RSMAR-I.

[MOS23] A. Montoison, D. Orban, and M. A. Saunders. *MINARES: An iterative solver for symmetric linear systems*. arXiv:2310.01757, 2023.

Numerical experiments

- A boundary value problem

$$\begin{cases} \Delta u + d \frac{\partial u}{\partial x} = f, & \text{in } \Omega := [0, 1] \times [0, 1], \\ u(x, 0) = u(x, 1), & \text{for } 0 \leq x \leq 1, \\ u(0, y) = u(1, y), & \text{for } 0 \leq y \leq 1, \end{cases}$$

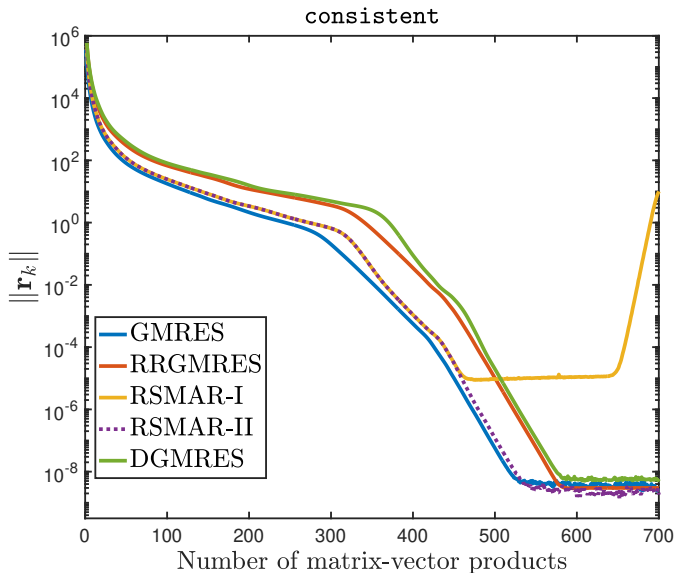
where d is a constant and f is a given function. [BW97]

- FD discretization yields a singular range-symmetric \mathbf{A} :

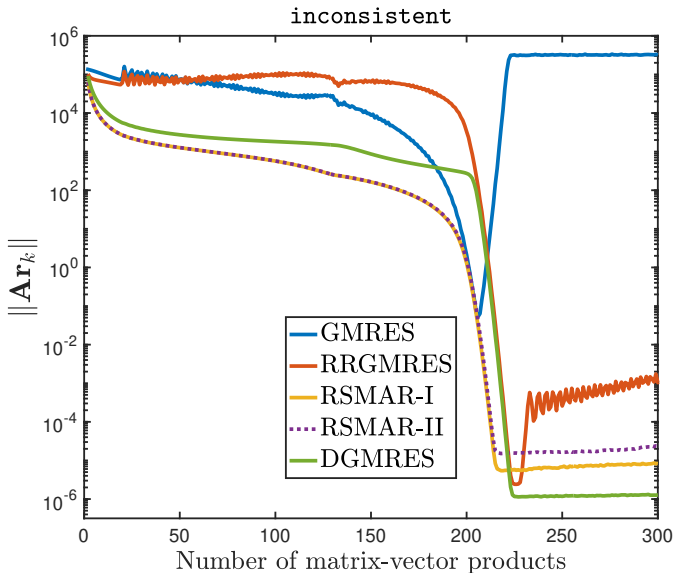
$$\mathbf{A} = \begin{bmatrix} \mathbf{T}_m & \mathbf{I}_m & & \mathbf{I}_m \\ \mathbf{I}_m & \ddots & \ddots & \\ & \ddots & \ddots & \mathbf{I}_m \\ \mathbf{I}_m & & \mathbf{I}_m & \mathbf{T}_m \end{bmatrix}, \quad \mathbf{T}_m = \begin{bmatrix} -4 & \alpha_+ & & \alpha_- \\ \alpha_- & \ddots & \ddots & \\ & \ddots & \ddots & \alpha_+ \\ \alpha_+ & & \alpha_- & -4 \end{bmatrix},$$

where $m = 100$, $h = 1/m$, $\alpha_{\pm} = 1 \pm dh/2$, and $d = 10$.

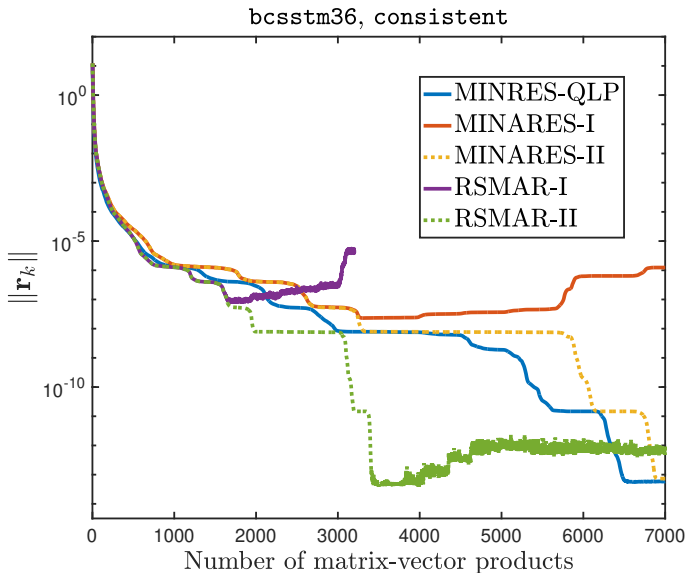
Convergence history for a consistent system



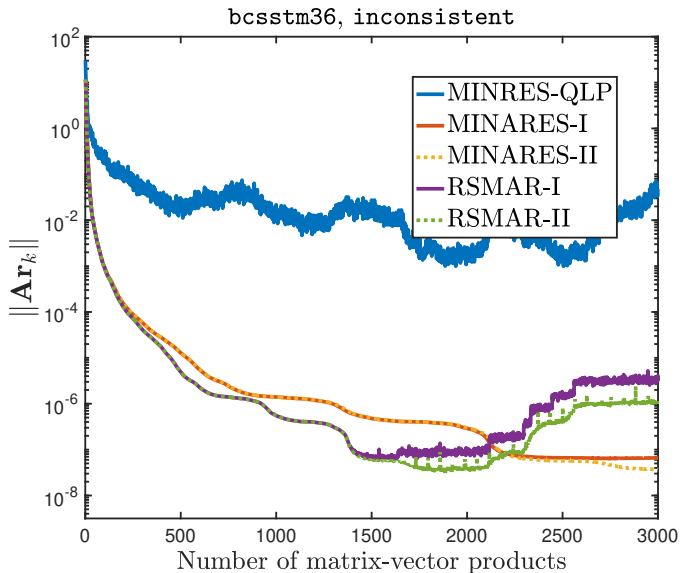
Convergence history for an inconsistent system



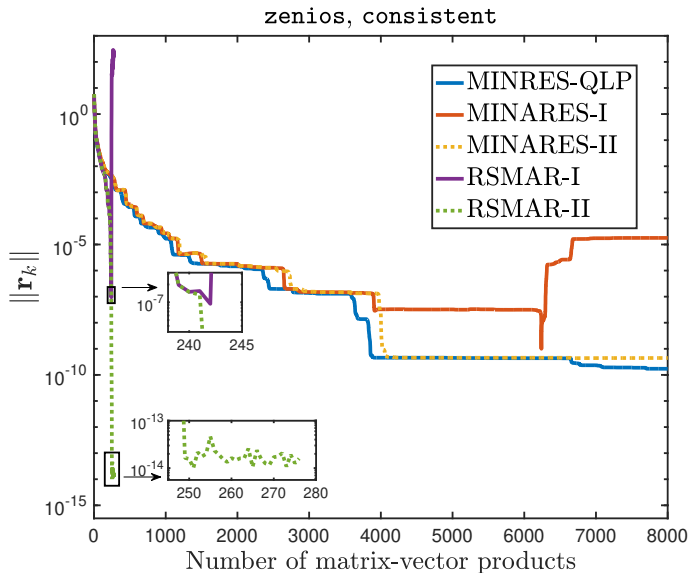
More numerical results



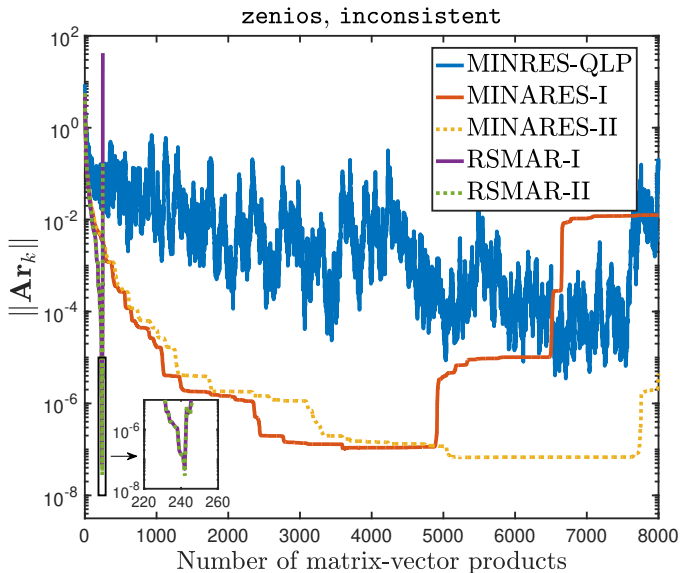
More numerical results



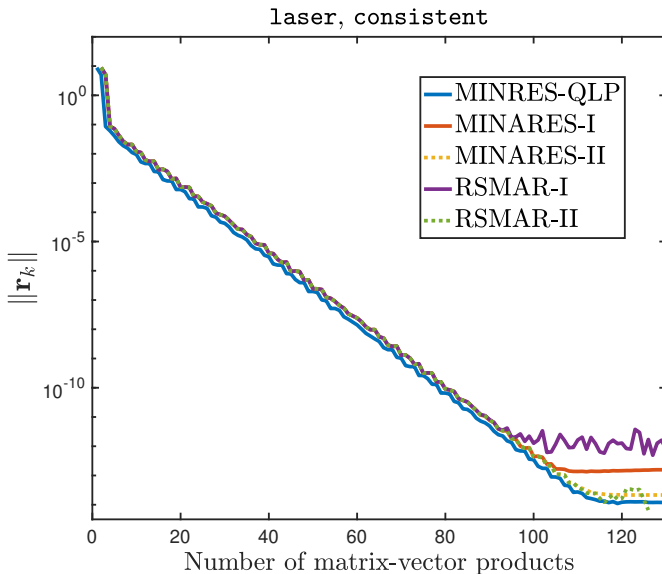
More numerical results



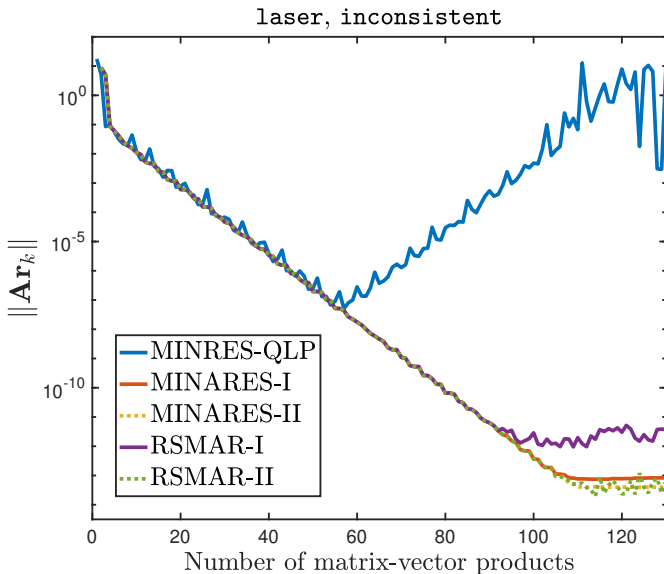
More numerical results



More numerical results



More numerical results



Summary

- RSMAR enriches the family of Krylov subspace methods for range-symmetric systems.
- For range-symmetric linear systems, the final iterates of RSMAR and GMRES are the same.
- For range-symmetric \mathbf{A} ,
 - (i) if $\mathbf{b} \in \text{range}(\mathbf{A})$, the final iterate of RSMAR is $\mathbf{A}^\dagger \mathbf{b}$, and
 - (ii) if $\mathbf{b} \notin \text{range}(\mathbf{A})$, the final iterate of RSMAR is a least squares solution and a lifting strategy can be used to obtain $\mathbf{A}^\dagger \mathbf{b}$.

Summary

- On singular inconsistent range-symmetric systems, RSMAR outperforms GMRES, RRGMR, and DGMRES, and thus should be the preferred method in finite precision arithmetic.
- RSMAR-II is better than RSMAR-I in finite precision arithmetic.
- Possible research directions:
 - (1) preconditioning
 - (2) stopping criteria
 - (3) performance for linear discrete ill-posed problems

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Our manuscript, slides, and MATLAB codes

- K. Du, J.-J. Fan, and F. Wang.

Obtaining the pseudoinverse solution of singular range-symmetric linear systems with GMRES-type methods.
arXiv:2401.11788, 2024.

- The slides are available at
<https://kuidu.github.io/talk.html>
- The MATLAB codes are available at
<https://kuidu.github.io/code.html>