

Beyond AMLS: Domain decomposition with rational filtering

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Acknowledgments

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Contents

- 1 Introduction and preliminary discussion
- 2 The domain decomposition (DD) framework
- 3 Combining domain decomposition with rational filtering
- 4 Numerical experiments

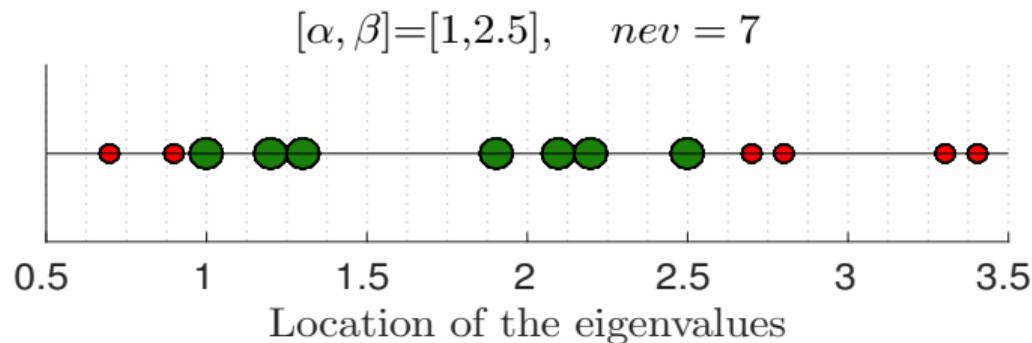
The algebraic generalized eigenvalue problem

The symmetric generalized eigenvalue problem is formally defined as

$$Ax = \lambda Mx.$$

Matrices A and M are assumed sparse and symmetric, while M is also SPD.

- The pencil (A, M) has n eigenpairs which we will denote by $(\lambda_i, x^{(i)})$, $i = 1, \dots, n$.
- We are only interested in computing those eigenpairs $(\lambda_i, x^{(i)})$ for which $\lambda_i \in [\alpha, \beta]$.
- We will denote the number of eigenvalues which satisfy the above property by 'nev'.



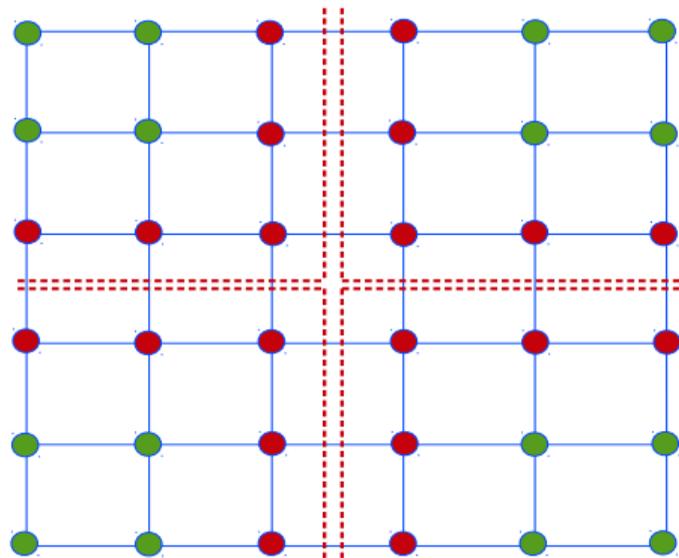
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Reordering equations/unknowns ($p \geq 2$ subdomains)

$$A = \begin{pmatrix} B_1 & & & E_1 \\ & B_2 & & E_2 \\ & & \ddots & \vdots \\ & & & B_p & E_p \\ E_1^T & E_2^T & \dots & E_p^T & C \end{pmatrix},$$

$$M = \begin{pmatrix} M_B^{(1)} & & & M_E^{(1)} \\ & M_B^{(2)} & & M_E^{(2)} \\ & & \ddots & \vdots \\ & & & M_B^{(p)} & M_E^{(p)} \\ (M_E^{(1)})^T & (M_E^{(2)})^T & \dots & (M_E^{(p)})^T & M_C \end{pmatrix}.$$



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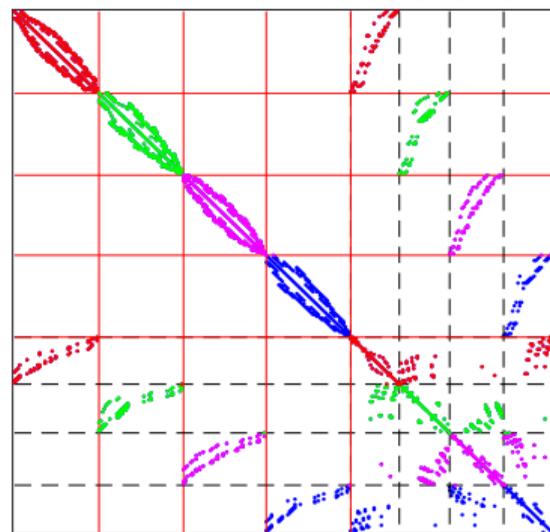
Notation: write as

$$A = \begin{pmatrix} B & E \\ E^T & C \end{pmatrix}, M = \begin{pmatrix} M_B & M_E \\ M_E^T & M_C \end{pmatrix},$$

$$x^{(i)} = \begin{pmatrix} u^{(i)} \\ y^{(i)} \end{pmatrix} = \begin{pmatrix} u_1^{(i)} \\ \vdots \\ u_p^{(i)} \\ y_1^{(i)} \\ \vdots \\ y_p^{(i)} \end{pmatrix}.$$

An example of the sparsity pattern of A and M for $p = 4$

$$A = \begin{pmatrix} B & E \\ E^T & C \end{pmatrix} = \begin{pmatrix} B_1 & & & & E_1 \\ & B_2 & & & E_2 \\ & & \dots & & \vdots \\ & & & B_p & E_p \\ E_1^T & E_2^T & \dots & E_p^T & C \end{pmatrix}$$

Sparsity pattern of matrix $|A| + |M|$ 

Invariant subspaces from a Schur complement viewpoint

$$(A - \lambda_i M)x^{(i)} = \begin{pmatrix} B - \lambda_i M_B & E - \lambda_i M_E \\ E^T - \lambda_i M_E^T & C - \lambda_i M_C \end{pmatrix} \begin{pmatrix} u^{(i)} \\ y^{(i)} \end{pmatrix} = 0.$$

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$$\left[C - \lambda_i M_C - \underbrace{(E - \lambda_i M_E)^T (B - \lambda_i M_B)^{-1} (E - \lambda_i M_E)}_{\text{block-diagonal}} \right] y^{(i)} = 0,$$

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To compute the eigenpairs $(\lambda_i, x^{(i)})_{i=1, \dots, nev}$

Perform a Rayleigh-Ritz projection onto $\mathcal{Z} = \mathcal{U} \oplus \mathcal{Y}$:

$$\mathcal{Y} = \text{span} \left\{ y^{(i)} \right\}_{i=1, \dots, nev},$$

$$\mathcal{U} = \text{span} \left\{ -(B - \lambda_i M_B)^{-1} (E - \lambda_i M_E) y^{(i)} \right\}_{i=1, \dots, nev}.$$

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Rational filtering

- We consider the following rational filter

$$\rho(\zeta) = \sum_{\ell=1}^{2N_c} \frac{\omega_\ell}{\zeta - \zeta_\ell} \approx \underbrace{\frac{1}{2\pi i} \int_{\Gamma_{[\alpha, \beta]}} \frac{1}{\nu - \zeta} d\nu}_{l_{[\alpha, \beta]}(\zeta)}$$

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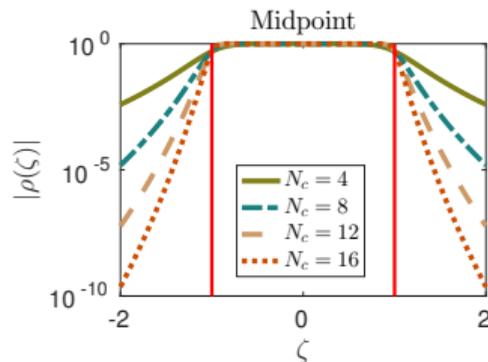
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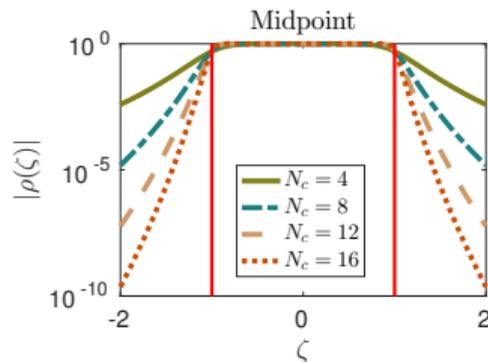


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- It is possible to apply $\rho(\cdot)$ to (A, M) :

$$\rho(M^{-1}A) = 2\Re e \left\{ \sum_{\ell=1}^{N_c} \omega_\ell (A - \zeta_\ell M)^{-1} M \right\}.$$

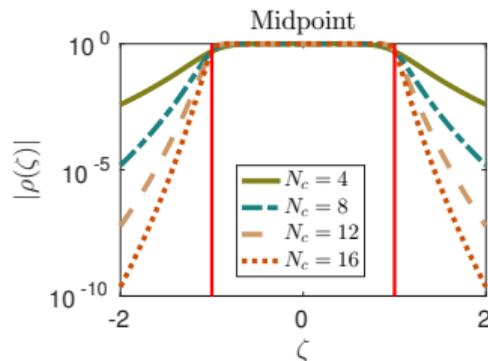
- Examples: FEAST (Subspace Iteration), Sakurai-Sugiura (Moments-based).
- Krylov projection schemes are also possible (RF-KRYLOV).

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- Examples: FEAST (Subspace Iteration), Sakurai-Sugiura (Moments-based).
- Krylov projection schemes are also possible (RF-KRYLOV).
- Our idea: **Decouple application of $\rho(\zeta)$ to interior/interface variables.**
- Potential advantages:
 - Reduced use of complex arithmetic.
 - Orthonormalization of shorter vectors (interface variables).
 - Faster convergence.

Summary of the proposed technique

- Our goal is to construct a subspace $\mathcal{Z} = \mathcal{U} \oplus \mathcal{Y}$ to perform a Rayleigh-Ritz projection onto.
- Recall that, ideally,

$$\mathcal{Y} = \text{span} \left\{ y^{(i)} \right\}_{i=1, \dots, nev},$$

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The technique proposed in this talk:

- 1 Constructs \mathcal{Y} by applying the rational filter $\rho(\zeta)$ to the interface region (Schur complement matrices).
- 2 Uses the above subspace to construct \mathcal{U} . This step is performed in real arithmetic and is embarrassingly parallel.

How to approximate $\text{span} \{y^{(1)}, \dots, y^{(nev)}\}$ (I)

Let $\zeta \in \mathbb{C}$ and define

$$B_\zeta = B - \zeta M_B, \quad E_\zeta = E - \zeta M_E, \quad C_\zeta = C - \zeta M_C, \\ S(\zeta) = C_\zeta - E_\zeta^T B_\zeta^{-1} E_\zeta.$$

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Then,

$$(A - \zeta M)^{-1} = \begin{pmatrix} B_\zeta^{-1} + B_\zeta^{-1} E_\zeta S(\zeta)^{-1} E_\zeta^T B_\zeta^{-1} & -B_\zeta^{-1} E_\zeta S(\zeta)^{-1} \\ -S(\zeta)^{-1} E_\zeta^T B_\zeta^{-1} & S(\zeta)^{-1} \end{pmatrix}.$$

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The matrix inverse $(A - \zeta M)^{-1}$ can be also written as:

$$(A - \zeta M)^{-1} = \sum_{i=1}^n \frac{1}{\lambda_i - \zeta} x^{(i)} (x^{(i)})^T = \sum_{i=1}^n \frac{1}{\lambda_i - \zeta} \begin{bmatrix} u^{(i)} (u^{(i)})^T & u^{(i)} (y^{(i)})^T \\ y^{(i)} (u^{(i)})^T & y^{(i)} (y^{(i)})^T \end{bmatrix}.$$

How to approximate $\text{span} \{y^{(1)}, \dots, y^{(nev)}\}$ (II)

Recall that

$$\rho(M^{-1}A) = 2\Re \left\{ \sum_{\ell=1}^{N_c} \omega_{\ell} (A - \zeta_{\ell} M)^{-1} M \right\}.$$

Combining altogether we get:

$$\rho(M^{-1}A) = 2\Re \left\{ \sum_{\ell=1}^{N_c} \omega_{\ell} \begin{bmatrix} B_{\zeta_{\ell}}^{-1} + B_{\zeta_{\ell}}^{-1} E_{\zeta_{\ell}} S(\zeta_{\ell})^{-1} E_{\zeta_{\ell}}^T B_{\zeta_{\ell}}^{-1} & -B_{\zeta_{\ell}}^{-1} E_{\zeta_{\ell}} S(\zeta_{\ell})^{-1} \\ -S(\zeta_{\ell})^{-1} E_{\zeta_{\ell}}^T B_{\zeta_{\ell}}^{-1} & \boxed{S(\zeta_{\ell})^{-1}} \end{bmatrix} \right\} M$$

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How to approximate $\text{span} \{y^{(1)}, \dots, y^{(nev)}\}$ (III)

Equating blocks leads to:

$$2\Re \left\{ \sum_{\ell=1}^{N_c} \omega_{\ell} S(\zeta_{\ell})^{-1} \right\} = \sum_{i=1}^n \rho(\lambda_i) y^{(i)} (y^{(i)})^T.$$

Since $\rho(\lambda_1), \dots, \rho(\lambda_{nev}) \neq 0$:

$$\text{span} \{y^{(1)}, \dots, y^{(nev)}\} \subseteq \text{range} \left(2\Re \left\{ \sum_{\ell=1}^{N_c} \omega_{\ell} S(\zeta_{\ell})^{-1} \right\} \right).$$

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Capture range $\left(\Re \left\{ \sum_{\ell=1}^{N_c} \omega_{\ell} S(\zeta_{\ell})^{-1} \right\} \right)$ by a Krylov projection scheme.

How to approximate $\text{span} \{y^{(1)}, \dots, y^{(nev)}\}$ (IV)

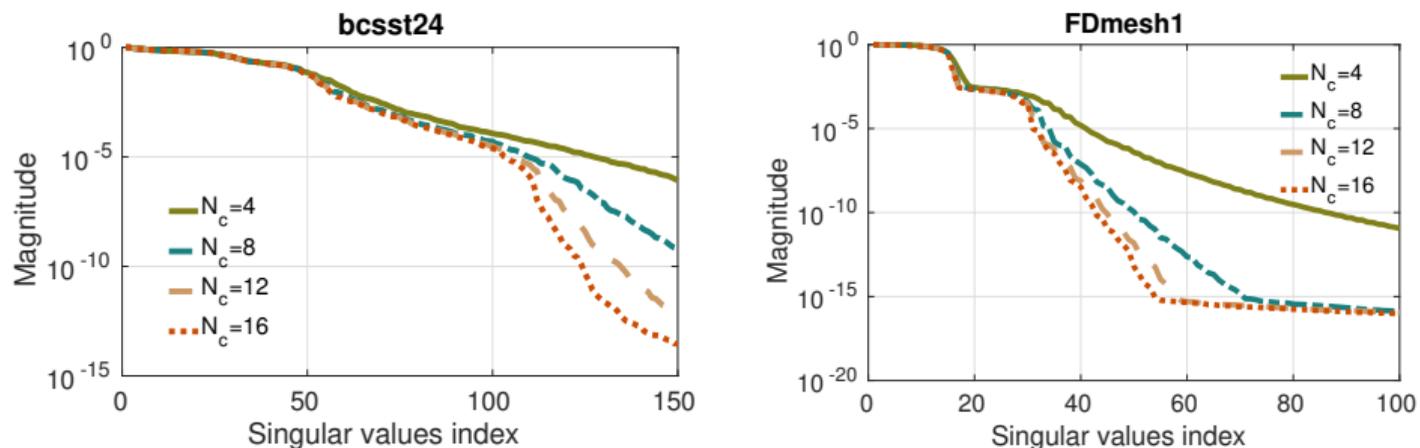


Figure: Leading singular values of $2\Re \left\{ \sum_{\ell=1}^{N_c} \omega_{\ell} \mathcal{S}(\zeta_{\ell})^{-1} \right\} = \sum_{i=1}^n \rho(\lambda_i) y^{(i)} (y^{(i)})^T$, $([\alpha, \beta] = [\lambda_1, \lambda_{100}])$.

How to approximate span $\{y^{(1)}, \dots, y^{(nev)}\}$ (IV)

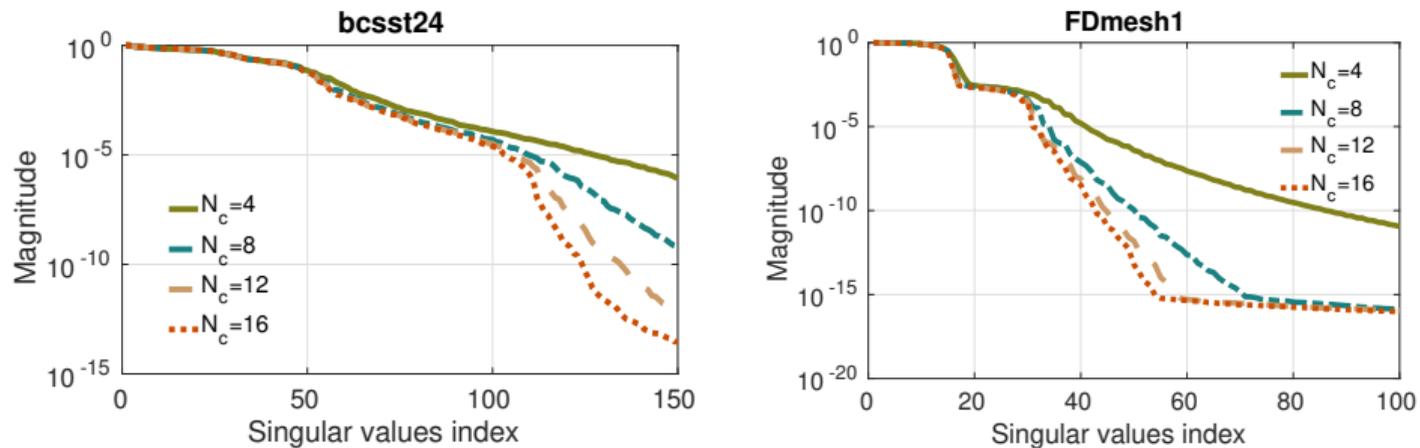


Figure: Leading singular values of $2\Re\left\{\sum_{\ell=1}^{N_c} \omega_{\ell} \mathcal{S}(\zeta_{\ell})^{-1}\right\} = \sum_{i=1}^n \rho(\lambda_i) y^{(i)} (y^{(i)})^T$, $([\alpha, \beta] = [\lambda_1, \lambda_{100}])$.

What if $\text{rank}\left(\left[y^{(1)}, \dots, y^{(nev)}\right]\right) < nev$?

Finalizing the proposed scheme (RF-DDES)

- Ideally, $\mathcal{U} = \{u^{(1)}, \dots, u^{(nev)}\}$, where

$$\begin{aligned}u^{(i)} &= -B_{\lambda_i}^{-1} E_{\lambda_i} y^{(i)} \\ &= -\left(B_{\lambda_i}^{-1} E_{\sigma} + (\lambda_i - \sigma) B_{\lambda_i}^{-1} M_E\right) y^{(i)}.\end{aligned}$$

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- We finally set $\mathcal{U} = \text{span}([V, U_1, U_2])$ where

$$U_1 = -[B_{\sigma}^{-1} E_{\sigma} Y, \dots, (B_{\sigma}^{-1} M_B)^{\psi-1} B_{\sigma}^{-1} E_{\sigma} Y],$$

$$U_2 = [B_{\sigma}^{-1} M_E Y, \dots, (B_{\sigma}^{-1} M_B)^{\psi-1} B_{\sigma}^{-1} M_E Y],$$

- V includes the eigenvectors associated with the $nev_B p$ smallest eigenvalues of (B_{σ}, M_B) .

Finalizing the proposed scheme (RF-DDES)

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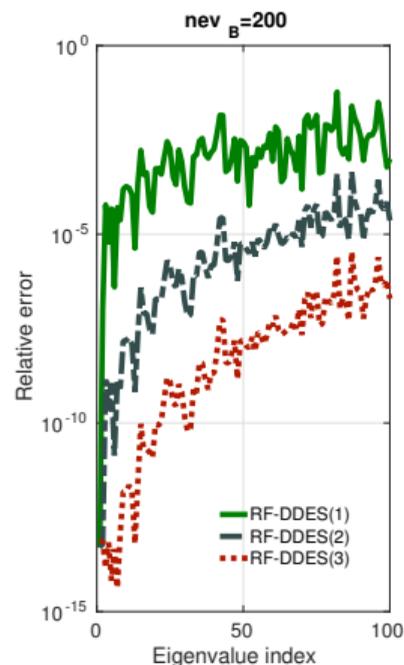
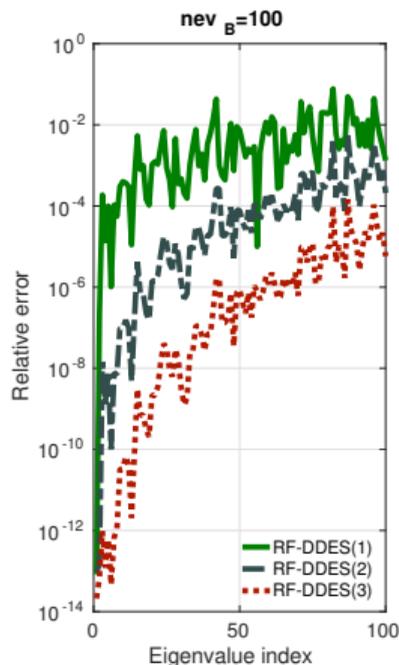
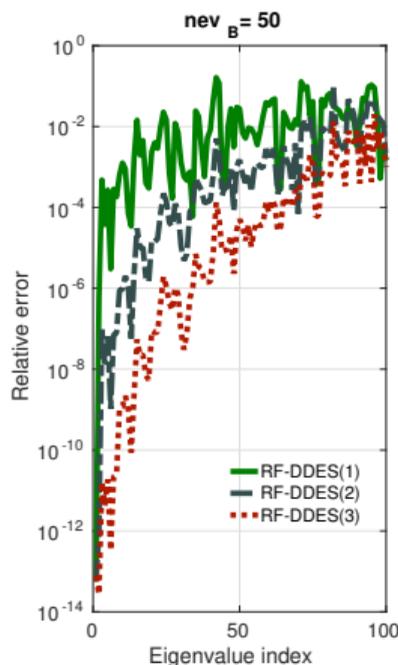
- V includes the eigenvectors associated with the $nev_B p$ smallest eigenvalues of (B_{σ}, M_B) .

$$\left\| u^{(i)} - \hat{u}^{(i)} \right\|_{M_B} \leq \max_{\ell \geq (nev_B p) + 1} O \left(\frac{(\lambda_i - \sigma)^{\psi+1}}{(\delta_{\ell} - \lambda_i)(\delta_{\ell} - \sigma)^{\psi}} \right).$$

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Approximation of the $nev = 100$ algebraically smallest eigenvalues of pencil qa8fk/qa8fm



A comparison of RF-KRYLOV and RF-DDES (I)

Table: Wall-clock times of RF-KRYLOV and RF-DDES using $\tau = 2, 4, 8, 16$ and $\tau = 32$ computational cores. RFD(2) and RFD(4) denote RF-DDES with $p = 2$ and $p = 4$ subdomains, respectively.

Matrix	$nev = 100$			$nev = 200$			$nev = 300$		
	RFK	RFD(2)	RFD(4)	RFK	RFD(2)	RFD(4)	RFK	RFD(2)	RFD(4)
shipsec8($\tau = 2$)	114	195	-	195	207	-	279	213	-
($\tau = 4$)	76	129	93	123	133	103	168	139	107
($\tau = 8$)	65	74	56	90	75	62	127	79	68
($\tau = 16$)	40	51	36	66	55	41	92	57	45
($\tau = 32$)	40	36	28	62	41	30	75	43	34
boneS01($\tau = 2$)	94	292	-	194	356	-	260	424	-
($\tau = 4$)	68	182	162	131	230	213	179	277	260
($\tau = 8$)	49	115	113	94	148	152	121	180	187
($\tau = 16$)	44	86	82	80	112	109	93	137	132
($\tau = 32$)	51	66	60	74	86	71	89	105	79

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FDmesh2($\tau = 2$)	241	85	-	480	99	-	731	116	-
($\tau = 4$)	159	34	63	305	37	78	473	43	85
($\tau = 8$)	126	22	23	228	24	27	358	27	31
($\tau = 16$)	89	16	15	171	17	18	256	20	21
($\tau = 32$)	51	12	12	94	13	14	138	15	20
FDmesh3($\tau = 2$)	1021	446	-	2062	502	-	3328	564	-
($\tau = 4$)	718	201	281	1281	217	338	1844	237	362
($\tau = 8$)	423	119	111	825	132	126	1250	143	141
($\tau = 16$)	355	70	66	684	77	81	1038	88	93
($\tau = 32$)	177	47	49	343	51	58	706	62	82

Amount of time spent on orthonormalization

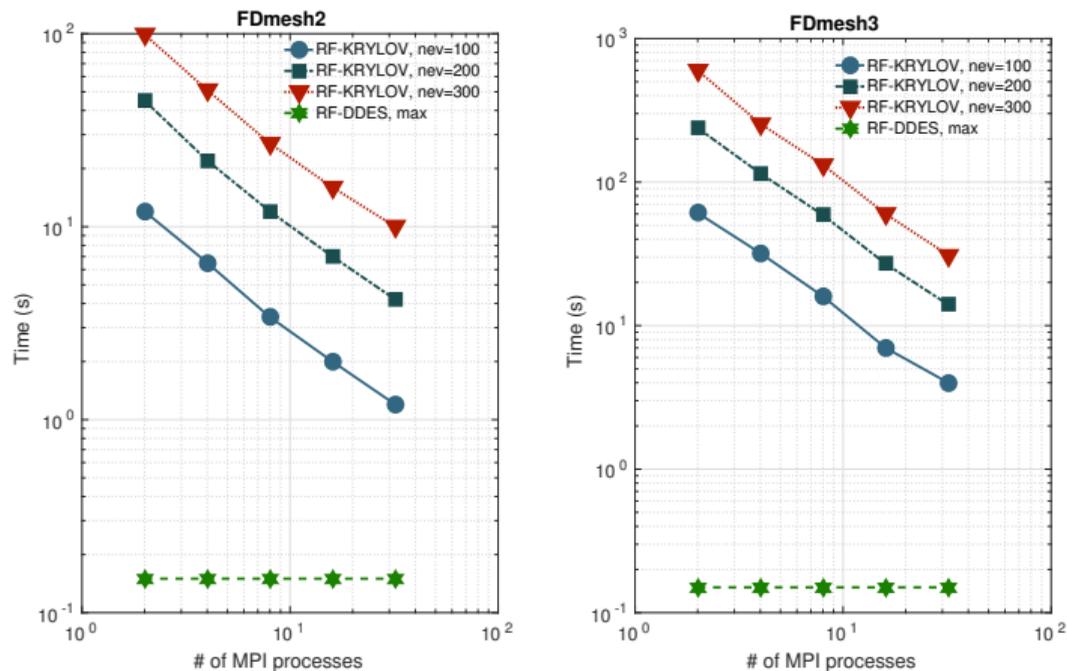


Figure: Left: “FDmesh2” ($n = 250,000$). Right: “FDmesh3” ($n = 1,000,000$).

Thank you

Questions?