

# Structure preserving GMRES methods for solving large Lyapunov equations

Matthias Bollhöfer, André Eppler

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Bundesministerium  
für Bildung  
und Forschung

- 1 Motivation
- 2 GMRES in low rank arithmetics
  - GMRES
  - LR-CF-ADI
- 3 Numerical results

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## Basic Idea of Model reduction

Linear circuit equations are modelled by a linear descriptor system:

$$\begin{aligned} \mathcal{E}\dot{x} &= \mathcal{A}x + \mathcal{B}u \\ y &= \mathcal{C}x \end{aligned} \quad \begin{aligned} \mathcal{E}, \mathcal{A} &\in \mathbb{R}^{n,n}, & \mathcal{B} &\in \mathbb{R}^{n,m} \\ \mathcal{C} &\in \mathbb{R}^{p,n} & & \end{aligned}$$

Approximate it by a reduced order system:

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## Balanced truncation

- Compute a system equivalence transformation and truncate the system.
- E singular:  
Requires the solution of 2 dual continuous-time algebraic Lyapunov equations (Proper Gramians) and 2 dual discrete-time algebraic Lyapunov equations (Improper Gramians).

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## Generalized projected Lyapunov equations

$$EXA^T + AXET = -P_l BB^T P_l^T, \quad X_p = P_r^T X P_r$$

$$E^T YA + A^T YE = -P_r^T C^T C P_r, \quad Y_p = P_l Y P_l^T$$

$$E, A \in R^{n \times n} \quad B, C^T \in R^{n \times n_s}$$

- r.h.s. is symmetric and low rank i.e.  $n_s \ll n$
- $E$  singular
- $P_r, P_l$  are projectors on right and left deflating subspaces of  $\lambda E - A$  corresponding to finite eigenvalues
- $\lambda E - A$  asymptotically stable: the solution exists and is unique

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$\mathcal{L} := A \otimes E + E \otimes A \dots$  Lyapunov operator  
 $\mathcal{X}_p = \text{vec}(X_p) \quad \mathcal{B}_p = \text{vec}(B_p B_p^T)$

Lyapunov equation

$$EX_p A^T + AX_p E^T = -B_p B_p^T$$

$$E, A \in R^{n \times n} \quad B_p \in R^{n \times n_s}$$

Linear equation

$$\mathcal{L} \mathcal{X}_p = -\mathcal{B}_p$$

$$\mathcal{L} \in R^{n^2 \times n^2} \quad \mathcal{B}_p \in R^{n^2 \times 1}$$

# Structure preservation principle

- Properties of  $X_p$ : low rank, symmetric, positive semidefinite
- Linear combination and matrix-vector multiplication preserve low rank and symmetry
- Objective: Structure preserving Krylov-subspace methods, e.g. GMRES
- Use factorization  $\mathcal{X} = VZV^T = \begin{matrix} \square & \square & \square \end{matrix}$

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## Properties

- Iterative method for solving  $\mathcal{L}\mathcal{X}_p = -\mathcal{B}_p$
- Calculates an orthonormal basis of m-dimensional Krylov space  
 $\mathcal{K}_m(\mathcal{R}_0, \mathcal{L}) = \text{span}(\mathcal{R}_0, \mathcal{L}\mathcal{R}_0, \dots, \mathcal{L}^{m-1}\mathcal{R}_0)$
- Solution  $\mathcal{X}_m$  minimizes residual.

## Algorithm

- Initialize: choose  $\mathcal{X}_0$  and dimension  $m$
- Arnoldi process:
  - 1 compute  $\mathcal{R}_0 = \mathcal{B}_p - \mathcal{L}\mathcal{X}_0$ ,  $h_{1,0} = \|\mathcal{R}_0\|$ ,  $\mathcal{V}_1 = \frac{\mathcal{R}_0}{h_{1,0}}$
  - 2 for  $j = 1 \dots m$ 
    - a) solve  $\mathcal{W}_j = M^{-1}\mathcal{V}_j$
    - b) compute  $\mathcal{V}_{j+1} = \mathcal{L}\mathcal{W}_j$
    - c) orthogonalize  $\mathcal{V}_{j+1}$  on all previous  $\mathcal{V}_i$  via MGS
  - 3 Let  $W_m := [\mathcal{W}_1 \dots \mathcal{W}_m]$
- Compute solution  $\mathcal{X}_m = \mathcal{X}_0 + W_m \mathcal{Y}_m$  with  $\mathcal{Y}_m$  minimizes  $\|h_{1,0}e_1 - H_m \mathcal{Y}\|$
- Restart : If *not converged*  $\mathcal{X}_0 = \mathcal{X}_m$

We only need 4 types of operations to formulate Krylov-subspace methods in low rank arithmetics.

## Tools LR-BLAS

- |   |   |  |
|---|---|--|
| 1 | $\mathcal{Y} = \mathcal{Y} + \alpha\mathcal{X}$                 | Addition                                 |
| 2 | $\mathcal{Y} = \alpha\mathcal{L}\mathcal{X} + \beta\mathcal{Y}$ | Generalized matrix-vector multiplication |
| 3 | $\alpha = \ \mathcal{Y}\ $                                      | Norm                                     |
| 4 | $\alpha = (\mathcal{Y}, \mathcal{X})$                           | Scalar product                           |

After 1) and 2) the rank of the result may increase. Strategy?

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# Rank truncation strategy

Rank of  $\mathcal{X} = \mathbf{VZV}^T$  need to be reduced w.r.t. given tolerance.

- Perform  $\mathbf{QR}\Pi$  decomposition of  $\mathbf{V} = \mathbf{QR}\Pi$

take first  $r_1$  rows of  $\mathbf{R}$

$$\hat{\mathbf{Q}} = \mathbf{Q}(:, 1:r_1), \hat{\mathbf{R}} = \mathbf{R}(1:r_1, :)$$

- Compute EVD of  $\hat{\mathbf{R}}\mathbf{Z}\hat{\mathbf{R}}^T = \mathbf{U}\Sigma\mathbf{U}^T$

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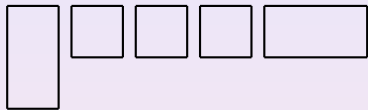
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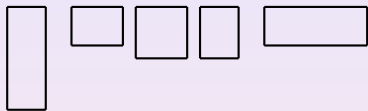
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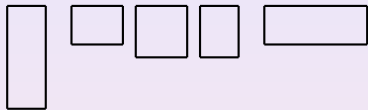
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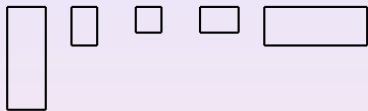
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## Result

- $\mathcal{X} = \hat{\mathbf{V}}\hat{\Sigma}\hat{\mathbf{V}}^T$  with  $\hat{\mathbf{V}} = \hat{\mathbf{Q}}\hat{\mathbf{U}}$
- $\hat{\mathbf{V}}$  unitary matrix
- $\hat{\Sigma}$  diagonal matrix

## Properties

- Must preserve structure (important fact)
- Should increase convergence rate
- Natural candidate: LRCF-ADI

Apply 1 cycle of LRCF-ADI to

$$EW_j A^T + AW_j E^T = -P_l \mathcal{V}_j P_l^T \quad P_r^T W_j P_r.$$

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## Alternating Direct Implicit

### Overview of Development

- Decompose linear equation into 2 (Finite Differences for elliptic PDE's) [Peacemen, Rachford '55]
- ADI-iteration for L. equations [Wachspress '88]

$$(E + \tau_j A)X_{j-\frac{1}{2}} = -B_\rho B_\rho^T - X_{j-1}(E - \tau_j A)^T$$

$$(E + \tau_j A)X_j = -B_\rho B_\rho^T - X_{j-\frac{1}{2}}^T(E - \tau_j A)^T$$

- Rewrite as one step iteration and work with low rank factors  $X_j = Z_j Z_j^T$  [Penzl' 99]
- Reversing the order of the shifts [Li, White '02]
- Apply to generalized L. equations [Benner '04, Stykel '08]

**Low Rank Cholesky Factor-Alternating Direct Implicit**  
computes the Cholesky-Factor  $Z$  of the solution  $X = ZZ^T$ .

## Algorithm

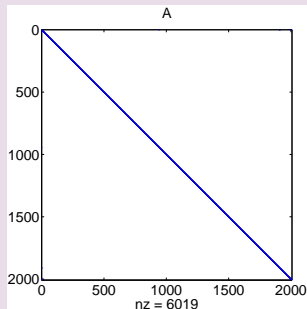
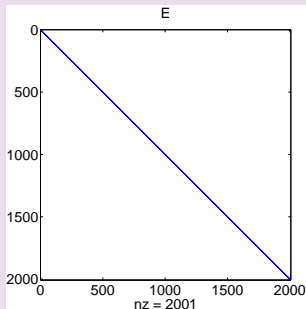
- 1 compute shift parameters  $\tau_1, \dots, \tau_j$
  - 2  $z_1 = \sqrt{-2\tau_1}(E + \tau_1 A)^{-1} B_p$   
 $Z = [z_1]$
  - 3 For  $i = 2 \dots j \dots$   
 $z_i = P_{i-1} z_{i-1}$ , with  
 $P_i = \frac{\sqrt{-2\tau_{i+1}}}{\sqrt{-2\tau_i}} [I - (\tau_{i+1} + \tau_i)(E + \tau_{i+1} A)^{-1} A]$   
 $Z = [Z \ z_i]$
- end for

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All computations were done on a workstation with Intel(R) Xeon(TM) MP CPU 3.66GHz and 16GB RAM using Matlab©Version 7.7.0.471 (R2008b).

## Example Circuit n=2007 RC-chain

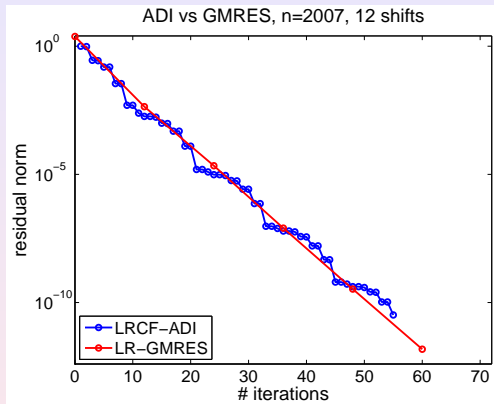
2002 capacitors, 2003 resistors, 3 voltage sources



NEC

Example circuits were provided by

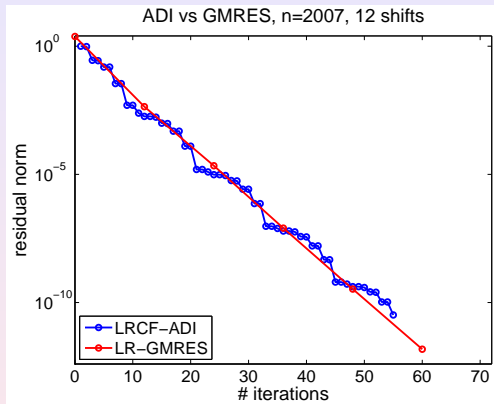
# Exact solve $E + \tau_i A$ (LU)



method	rank $X_\rho$	cpu-time [s]
LRCF-ADI	98	4,0
LR-GMRES	95	5,8

- same number of iterations
- comparable runtime
- convergence criterion cheaper

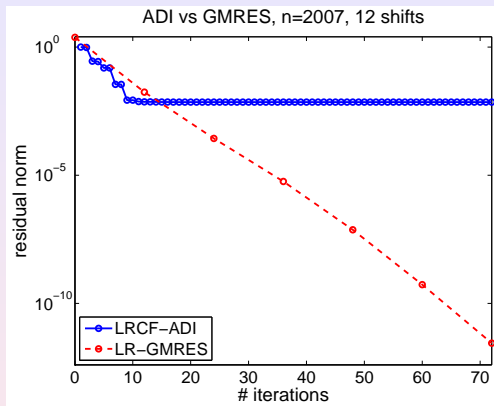
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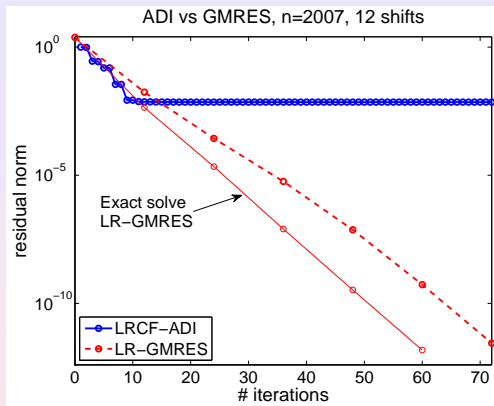


[\*M. Bollhöfer et.al. ILUPACK - preconditioning software package. Available online at <http://ilupack.tu-bs.de/>.

Release V2.2, November 2008. ]

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## Benefits

- Structure preservation (low rank, symmetry) is fulfilled
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- Same number of iterations as LR-CFADI together with a comparable runtime

## Future work

- Use QMR as Krylov subspace method
- Integration in PABTEC
- C implementation
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