



MAX PLANCK INSTITUTE
FOR DYNAMICS OF COMPLEX
TECHNICAL SYSTEMS
MAGDEBURG



COMPUTATIONAL METHODS IN
SYSTEMS AND CONTROL THEORY

Towards high performance IRKA on hybrid CPU-GPU systems

Jens Saak
in collaboration with

Georg Pauer
(OVGU/MPI Magdeburg)

Kapil Ahuja, Ruchir Garg
(IIT Indore)

Hartwig Anzt, Jack Dongarra
(ICL Uni Tennessee Knoxville)

Edmond Chow
(Georgia Tech)

17th GAMM Workshop on Applied and Numerical Linear Algebra
Cologne, Germany
September 7-8, 2017



Linear time-invariant (LTI) system:

$$E \dot{x}(t) = A x(t) + B u(t)$$

$$y(t) = C x(t)$$



$$\begin{aligned} E_r &= W^T E V \\ A_r &= W^T A V \\ B_r &= W^T B \\ C_r &= C V \end{aligned} \quad x(t) \in \mathbb{R}^n, x_r(t) \in \mathbb{R}^r, u \in \mathbb{R}^p, y, \tilde{y} \in \mathbb{R}^q$$

Reduced order model (ROM):

$$E_r \dot{x}_r(t) = A_r x_r(t) + B_r u(t)$$

$$\tilde{y}(t) = C_r x_r(t)$$



MOR of LTI systems often employs the rational Krylov subspace method (RKSM) of some flavor:

- Moment Matching (V, W span rational Krylov subspaces),
- IRKA (iterative rational Krylov algorithm)
- Balanced Truncation (computing the Gramians via ADI or RKSM)



MOR of LTI systems often employs the rational Krylov subspace method (RKSM) of some flavor:

- Moment Matching (V, W span rational Krylov subspaces),
- **IRKA** (iterative rational Krylov algorithm)
- Balanced Truncation (computing the Gramians via ADI or RKSM)

IRKA in a nutshell

e.g. [GUGERCIN/ANTOULAS/BEATTIE '08]

1. Guess initial ROM or initial shifts,
2. Compute
$$\text{span } V = \text{span}\{(\sigma_1 E - A)^{-1}B, \dots, (\sigma_r E - A)^{-1}B\},$$
$$\text{span } W = \text{span}\{(\sigma_1 E^T - A^T)^{-1}C^T, \dots, (\sigma_r E^T - A^T)^{-1}C^T\}.$$
3. Update ROM, set $\sigma = -\Lambda(A_r, E_r)$, repeat until σ has converged.



MOR of LTI systems often employs the rational Krylov subspace method (RKSM) of some flavor:

- Moment Matching (V, W span rational Krylov subspaces),
- IRKA (iterative rational Krylov algorithm)
- Balanced Truncation (computing the Gramians via ADI or RKSM)

Dominant computation in all these methods

Sequences of Shifted Linear Systems (SLS)

$$(A + \sigma_j E) X_j = Y_j, \quad \text{for } j \in \mathcal{I} \subset \mathbb{N},$$

with **real** data $A \in \mathbb{R}^{n \times n}$, $E \in \mathbb{R}^{n \times n}$, $Y_j \in \mathbb{R}^{n \times m}$, $m \ll n$, but possibly **complex** shifts $\sigma_j \in \mathbb{C}$.



MOR of LTI systems often employs the rational Krylov subspace method (RKSM) of some flavor:

- Moment Matching (V, W span rational Krylov subspaces),
- IRKA (iterative rational Krylov algorithm)
- Balanced Truncation (computing the Gramians via ADI or RKSM)

Dominant computation in all these methods

Sequences of Shifted Linear Systems (SLS)

$$P_j (A + \sigma_j E) X_j = P_j Y_j, \quad \text{for } j \in \mathcal{I} \subset \mathbb{N},$$

with **real** data $A \in \mathbb{R}^{n \times n}$, $E \in \mathbb{R}^{n \times n}$, $Y_j \in \mathbb{R}^{n \times m}$, $m \ll n$, but possibly **complex** shifts $\sigma_j \in \mathbb{C}$. Preconditioner $P_j \in \mathbb{R}^{n \times n}$ usually needs update for every j .



Sequences of Shifted Linear Systems (SLS)

$$P_j (A + \sigma_j E) X_j = P_j Y_j, \quad \text{for } j \in \mathcal{I} \subset \mathbb{N},$$

We aim at using iterative solvers on hybrid CPU-GPU systems.

Efficiency improving strategies

1. recycle / realign preconditioner P_j
2. recycle solvers / subspaces
3. solve shifted linear systems in parallel



Sequences of Shifted Linear Systems (SLS)

$$P_j (A + \sigma_j E) X_j = P_j Y_j, \quad \text{for } j \in \mathcal{I} \subset \mathbb{N},$$

We aim at using iterative solvers on hybrid CPU-GPU systems.

Efficiency improving strategies

1. recycle / realign preconditioner P_j

extending [ANZT/CHOW/S./DONGARRA '16]

2. recycle solvers / subspaces

3. solve shifted linear systems in parallel



Sequences of Shifted Linear Systems (SLS)

$$P_j (A + \sigma_j E) X_j = P_j Y_j, \quad \text{for } j \in \mathcal{I} \subset \mathbb{N},$$

We aim at using iterative solvers on hybrid CPU-GPU systems.

Efficiency improving strategies

1. recycle / realign preconditioner P_j

extending [ANZT/CHOW/S./DONGARRA '16]

2. recycle solvers / subspaces

following [AHUJA/DE STURLER/GUGERCIN/CHANG '12]

3. solve shifted linear systems in parallel



1. Introduction

Projection based Model Order Reduction (MOR)
Description of Today's Focus Problem
Strategies for the switched linear Systems

2. Reusing and Realigning Preconditioners

Prior Work and Our Approach
The Real aka. Symmetric Case
The Non-Symmetric aka. Complex Case
Structure Exploiting Preconditioner
Experiments

3. Recycling Solvers and Subspaces

Background
Preliminary Results

4. Parallel Solution of the Shifted Systems

1. reuse preconditioner for small matrix changes, i.e. similar shifts
2. update incomplete factorization preconditioner
[BELLAVIA/DE SIMONE/DI SERAFINO/MORINI '11, BENZI/BERTACCINI '03,
BERTACCINI '04, CALGARO/CHEHAB/SAAD '10,
DUINTJER TEBBENS/TÜMA '07]

Main Issues

- reuses reduce efficiency of the preconditioner
- updates have limited potential for parallel execution

Goal

highly parallel preconditioner update and application

Preconditioned iterative solution of

Sequences of Shifted Linear Systems (SLS)

$$P_j (A + \sigma_j E) X_j = P_j Y_j, \quad \text{for } j \in \mathcal{I} \subset \mathbb{N},$$

for A , E symmetric and σ_j real.

Idea: Minimize $\|A - U^T U\|$ via fixed point approach [CHOW/ET AL. '15]

Preconditioned iterative solution of

Sequences of Shifted Linear Systems (SLS)

$$P_j (A + \sigma_j E) X_j = P_j Y_j, \quad \text{for } j \in \mathcal{I} \subset \mathbb{N},$$

for A, E symmetric and σ_j real.

Idea: Minimize $\|A - U^T U\|$ via fixed point approach [CHOW/ET AL. '15]

Initialization

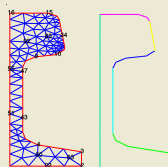
If $|\sigma_j - \sigma_{j-1}|$ is small enough, then $\|P_j - P_{j-1}\|$ is small
 $\Rightarrow P_{j-1}$ good initial guess for P_j .

Use [CHOW/PATEL '15, CHOW/ANZT/DONGARRA '15] for (asynchronous) iterative computation of incomplete factorization preconditioners.

	IC	Time [ms]			Speedup		
		Number of sweeps			Number of sweeps		
		1	3	5	1	3	5
371	4.88	0.03	0.06	0.08	167.70	87.14	57.48
1 357	9.01	0.03	0.06	0.08	309.62	158.07	107.39
5 177	15.60	0.04	0.08	0.12	421.62	200.00	134.48
20 209	32.00	0.08	0.19	0.30	405.58	167.54	105.26
79 841	66.40	0.23	0.62	1.01	286.21	106.58	65.74
317 377	142.00	0.78	2.25	3.73	182.75	63.11	38.07
1 265 537	323.00	2.94	8.77	14.50	109.86	36.83	22.28

Test example:

Oberwolfach Collection Steel Cooling Benchmark [BENNER/S. '05]
here using the FEniCS reimplementaion by Maximilian Behr





Consider

$$\mathcal{A}x = b$$

for $\mathcal{A} \in \mathbb{C}^{n \times n}$, $x, b \in \mathbb{C}^n$.

With $\mathcal{A}_r, \mathcal{A}_i \in \mathbb{R}^{n \times n}$, $x_r, x_i, b_r, b_i \in \mathbb{R}^n$ write

$$\mathcal{A} = \mathcal{A}_r + \imath \mathcal{A}_i, \quad x = x_r + \imath x_i, \quad b = b_r + \imath b_i.$$

Idea

e.g. [DAY/HEROUX '01, BENZI/BERTACCINI '08]

Rewrite to **real** linear system

$$\begin{bmatrix} \mathcal{A}_r & -\mathcal{A}_i \\ \mathcal{A}_i & \mathcal{A}_r \end{bmatrix} \begin{bmatrix} x_r \\ x_i \end{bmatrix} = \begin{bmatrix} b_r \\ b_i \end{bmatrix}$$

and employ block preconditioner.

In our special case

$$\mathcal{A}_{j,r} = A + \operatorname{Re}(\sigma_j) E, \quad \mathcal{A}_{j,i} = \operatorname{Im}(\sigma_j) E$$

Let

$$J_j = \begin{bmatrix} 0 & -\operatorname{Im}(\sigma_j) \\ \operatorname{Im}(\sigma_j) & 0 \end{bmatrix}.$$

Then

$$\begin{aligned} \mathcal{A}_j \tilde{V}_j = \tilde{W}_j &\Leftrightarrow \begin{bmatrix} \mathcal{A}_{j,r} & -\mathcal{A}_{j,i} \\ \mathcal{A}_{j,i} & \mathcal{A}_{j,r} \end{bmatrix} \begin{bmatrix} V_{j,r} \\ V_{j,i} \end{bmatrix} = \begin{bmatrix} W_{j,r} \\ W_{j,i} \end{bmatrix} \\ &\Leftrightarrow (I_2 \otimes \mathcal{A}_{j,r} + J_j \otimes E) \tilde{V}_j = \tilde{W}_j \end{aligned}$$



In our special case

$$\mathcal{A}_{j,r} = A + \operatorname{Re}(\sigma_j) E, \quad \mathcal{A}_{j,i} = \operatorname{Im}(\sigma_j) E$$

Let

$$J_j = \begin{bmatrix} 0 & -\operatorname{Im}(\sigma_j) \\ \operatorname{Im}(\sigma_j) & 0 \end{bmatrix}.$$

Then

$$\begin{aligned} \mathcal{A}_j \tilde{V}_j = \tilde{W}_j &\Leftrightarrow \begin{bmatrix} \mathcal{A}_{j,r} & -\mathcal{A}_{j,i} \\ \mathcal{A}_{j,i} & \mathcal{A}_{j,r} \end{bmatrix} \begin{bmatrix} V_{j,r} \\ V_{j,i} \end{bmatrix} = \begin{bmatrix} W_{j,r} \\ W_{j,i} \end{bmatrix} \\ &\Leftrightarrow (I_2 \otimes \mathcal{A}_{j,r} + J_j \otimes E) \tilde{V}_j = \tilde{W}_j \end{aligned}$$

$$\text{Idea: } P := (I_2 \otimes \mathcal{A}_{j,r})^{-1} = (I_2 \otimes \mathcal{A}_{j,r}^{-1})$$



In our special case

$$\mathcal{A}_{j,r} = A + \operatorname{Re}(\sigma_j) E, \quad \mathcal{A}_{j,i} = \operatorname{Im}(\sigma_j) E$$

Let

counter diagonal blocks are:

$$\begin{aligned} \pm \operatorname{Im}(\sigma_j) (A + \operatorname{Re}(\sigma_j) E)^{-1} E &= \frac{\pm \operatorname{Im}(\sigma_j)}{\operatorname{Re}(\sigma_j)} (A + \operatorname{Re}(\sigma_j) E)^{-1} (A + \operatorname{Re}(\sigma_j) E - A) \\ &= \frac{\pm \operatorname{Im}(\sigma_j)}{\operatorname{Re}(\sigma_j)} (I_n - (A + \operatorname{Re}(\sigma_j) E)^{-1} A). \end{aligned}$$

$$\Leftrightarrow (I_2 \otimes \mathcal{A}_{j,r} + J_j \otimes E) \tilde{V}_j = \tilde{W}_j$$

$$\text{Idea: } P := (I_2 \otimes \mathcal{A}_{j,r})^{-1} = \left(I_2 \otimes \mathcal{A}_{j,r}^{-1} \right)$$

P3-GMRES iterations for SLS

(tol= 10^{-8} , maxiter=250)

	$-3.71 \cdot 10^2 + i 2.39 \cdot 10^2 / 10^{-2} / 10^{-6}$	$-3.71 \cdot 10^{-6} / 10^4 + 2.39 \cdot 10^2 i$
no prec.	174 136 136	250 11
block ILU(0)	54 41 41	130 5
block ILU(1)	35 26 26	85 4
block ILU(2)	26 19 19	65 4
block ILU(3)	21 14 14	54 4
block \	15 2 1	38 4
full ILU(0)	52 41 41	125 5

¹model data by Maximilian Behr



Recall IRKA needs:

$$\begin{aligned}\text{span } V &= \text{span}\{(\sigma_1 E - A)^{-1}B, \dots, (\sigma_k E - A)^{-1}B\}, \\ \text{span } W &= \text{span}\{(\sigma_1 E^T - A^T)^{-1}C^T, \dots, (\sigma_k E^T - A^T)^{-1}C^T\}.\end{aligned}$$



Recall IRKA needs:

$$\begin{aligned}\text{span } V &= \text{span}\{(\sigma_1 E - A)^{-1}B, \dots, (\sigma_k E - A)^{-1}B\}, \\ \text{span } W &= \text{span}\{(\sigma_1 E^T - A^T)^{-1}C^T, \dots, (\sigma_k E^T - A^T)^{-1}C^T\}.\end{aligned}$$

Idea

[AHUJA/DE STURLER/GUGERCIN/CHANG '12]

- Need to solve with dual operators \rightsquigarrow Use BiCG



Recall IRKA needs:

$$\begin{aligned}\text{span } V &= \text{span}\{(\sigma_1 E - A)^{-1}B, \dots, (\sigma_k E - A)^{-1}B\}, \\ \text{span } W &= \text{span}\{(\sigma_1 E^T - A^T)^{-1}C^T, \dots, (\sigma_k E^T - A^T)^{-1}C^T\}.\end{aligned}$$

Idea

[AHUJA/DE STURLER/GUGERCIN/CHANG '12]

- Need to solve with dual operators \rightsquigarrow Use BiCG
- MIMO systems (i.e., $p, q > 1$) repeatedly solve with different right hand sides \rightsquigarrow update subspace, i.e. recycle



Recall IRKA needs:

$$\begin{aligned}\text{span } V &= \text{span}\{(\sigma_1 E - A)^{-1}B, \dots, (\sigma_k E - A)^{-1}B\}, \\ \text{span } W &= \text{span}\{(\sigma_1 E^T - A^T)^{-1}C^T, \dots, (\sigma_k E^T - A^T)^{-1}C^T\}.\end{aligned}$$

Idea

[AHUJA/DE STURLER/GUGERCIN/CHANG '12]

- Need to solve with dual operators \rightsquigarrow Use BiCG
- MIMO systems (i.e., $p, q > 1$) repeatedly solve with different right hand sides \rightsquigarrow update subspace, i.e. recycle
- upon convergence: $\sigma_j^{(i)} \approx \sigma_j^{(i+1)}$ \rightsquigarrow employ deflation, i.e., recycle



Recall IRKA needs:

$$\begin{aligned}\text{span } V &= \text{span}\{(\sigma_1 E - A)^{-1}B, \dots, (\sigma_k E - A)^{-1}B\}, \\ \text{span } W &= \text{span}\{(\sigma_1 E^T - A^T)^{-1}C^T, \dots, (\sigma_k E^T - A^T)^{-1}C^T\}.\end{aligned}$$

Idea

[AHUJA/DE STURLER/GUGERCIN/CHANG '12]

- Need to solve with dual operators \rightsquigarrow Use BiCG
- MIMO systems (i.e., $p, q > 1$) repeatedly solve with different right hand sides \rightsquigarrow update subspace, i.e. recycle
- upon convergence: $\sigma_j^{(i)} \approx \sigma_j^{(i+1)}$ \rightsquigarrow employ deflation, i.e., recycle

RBiCG for IRKA

Current focus with Kapil Ahuja, Ruchir Garg and Georg Pauer: CUDA accelerated version

MATLAB[®] results

[AHUJA/DE STURLER/GUGERCIN/CHANG '12]

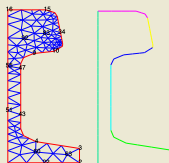
n	σ	r	drop tol	IRKA steps	iteration count			time(s)		
					BiCG	RBiCG	Ratio	BiCG	RBiCG	Ratio
20209	40	20	0.01	31	3032	1434	2.11	73.82	54.28	1.36
79841	50	20	0.005	44	6324	2547	2.48	742.83	505.09	1.47

Test example:

Oberwolfach Collection Steel Cooling Benchmark[BENNER/S. '05]

available from:

<https://portal.uni-freiburg.de/imteksimulation/downloads/benchmark/Steel%20Profiles%20%2838881%29>



**Observation:**

Iterative solver needs sparse matrix vector product $(A + \sigma_j E)x_j = y_j$.
 \rightsquigarrow memory bandwidth bounded.

Idea:

Define: $X = [x_1, \dots, x_r]$, $Y = [y_1, \dots, y_r]$ and $\Sigma = \text{diag}(\sigma)$

Then

$$Y = AX + EX\Sigma,$$

and

- sparse matrix vector product \rightsquigarrow sparse-dense matrix matrix product
- $2r$ sparse matrix sweeps become 2 sparse matrix sweeps

Requires short recurrence method (e.g. BiCG) to limit memory usage



Conclusions

- analysis of the problem structure gives rise to 3 promising implementation candidates
- Preconditioner realignment and Subspace recycling can even be combined

Outlook

- proper HPC implementation pending
- comparison of the strategies \rightsquigarrow Master Thesis Georg Pauer



Conclusions

- analysis of the problem structure gives rise to 3 promising implementation candidates
- Preconditioner realignment and Subspace recycling can even be combined

Outlook

- proper HPC implementation pending
- comparison of the strategies \rightsquigarrow Master Thesis Georg Pauer

Thank you for your attention!