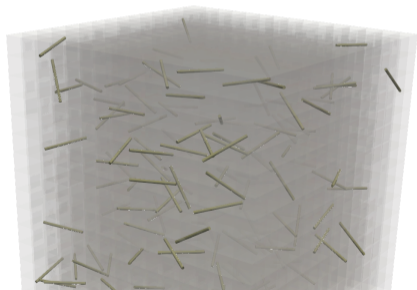


Physics-based block preconditioning for beam/solid interaction



Max Firmbach¹ Alexander Popp¹ Matthias Mayr^{1, 2}

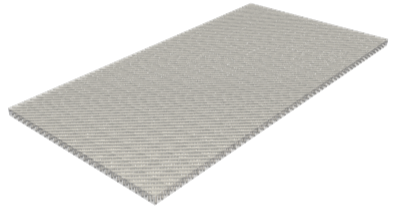
¹Institute for Mathematics and Computer-Based Simulation (IMCS), University of the Bundeswehr Munich

²Data Science & Computing Lab, University of the Bundeswehr Munich





- Beam / Solid interactions occur in a wide variety of scenarios:
 - Engineering (steel-reinforced concrete, composite materials)
 - Biomechanics (collagen fibers in connective tissue)
- Time-to-solution dominated by cost for linear solver
 - Scalability through multilevel methods
 - Algebraic Multigrid (AMG) for its flexibility
 - **But:** Ill-conditioned matrix due to discretization and penalty regularization prohibit out-of-the-box block smoothing



Goal

Scalable AMG method for beam / solid interaction problems in penalty formulation



The coupling of beam-like structures with solid continua is described with the following coupled linearized system for beam/solid interaction:

$$\begin{pmatrix} \mathbf{K}_S + \epsilon \mathbf{M}^T \kappa^{-1} \mathbf{M} & -\epsilon \mathbf{M}^T \kappa^{-1} \mathbf{D} \\ -\epsilon \mathbf{D}^T \kappa^{-1} \mathbf{M} & \mathbf{K}_B + \epsilon \mathbf{D}^T \kappa^{-1} \mathbf{D} \end{pmatrix} \begin{pmatrix} \Delta \mathbf{d}_S \\ \Delta \mathbf{d}_B \end{pmatrix} = - \begin{pmatrix} \mathbf{r}_S \\ \mathbf{r}_B \end{pmatrix}$$

Legend

$(\cdot)_S$	solid contribution
$(\cdot)_B$	beam contribution
\mathbf{d}	displacement DOFs
\mathbf{r}	residual
ϵ	penalty parameter
κ	scaling factor



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- **Solid DOFs**
- **Beam DOFs**
- **Coupling constraints**



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Challenges:

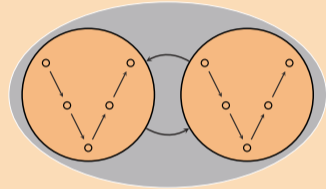
- Highly non-diagonal and ill-conditioned block matrix due to penalty regularization
- Block matrix may be nonsymmetric due to beam formulation



Approximations in Schur complement preconditioners

1. Approximation \hat{A} to form Schur complement \tilde{S}
 - ⇒ Governed by the type of block method
 - ⇒ e.g. $A \approx \hat{A} := \text{diag}(A)$
2. Approximate block inverses within Schur complement preconditioner by standard AMG
 - ⇒ Approximation quality can be controlled through the AMG settings

BlockMethod(AMG)¹



- Coupling constraints are considered on fine level only
- Block method can be:
 - ⇒ Block LU
 - ⇒ Uzawa
 - ⇒ SIMPLE

¹Wiesner, T. A.; Mayr, M.; Popp, A.; Gee, M. W. and Wall, W. A. (2021): "Algebraic multigrid methods for saddle point systems arising from mortar contact formulations", *Numerical Methods in Engineering*, 122, 15:3749-3779



Due to the penalty regularization using just a diagonal approximation of the inverse inside the Schur complement calculation is not sufficient:

- Sparse approximate inverse methods (SPAI²) can produce better approximation
- Use matrix graph of A to calculate inverse \hat{A} on this sparsity pattern
- Based on Frobenius norm minimization:

$$\min_{\hat{A} \in \mathcal{S}} \|A\hat{A} - I\|_F$$

with \mathcal{S} being the set of all sparse matrices with some known structure

²Grothe, M. J. and Huckle, T. (1997): "Parallel preconditioning with sparse approximate inverses", *Journal Of Scientific Computing*, 18, 3:838-853

Parallel computation

Decomposition into several least squares problems makes it inherently parallel:

$$\|A\hat{A} - I\|_F^2 = \sum_{k=1}^n \|(A\hat{A} - I)e_k\|_2^2,$$

for each row k solve

$$\min_{\hat{a}_k} \|A\hat{a}_k - e_k\|_2$$

with QR-decomposition



A priori pattern selection

Using just the pattern of A as input might not result in a satisfactory result, the matrix pattern needs to be enriched for a good sparse inverse approximation:

- Static approach by using recursive powers of graph of matrix $A \rightarrow$ recursion depth defined as level l
- Combining rows of graph $J(A)$ such that³:

$$J(A_{k,:}^l) = J(A_{k,:}^{l-1})J(A^{l-1})$$

- Pre- and post filtering of input graph and sparse inverse approximation with threshold value τ

SPAI with static pattern selection

1. Thresholding of $J(A)$
2. Determine graph of powers of A : $J(A^l)$
3. Calculate sparse inverse approximation \hat{A}
4. Post filtering of \hat{A}

³Chow E. (2001): "Parallel implementation and practical use of sparse approximate inverse preconditioners with a priori sparsity patterns", *The International Journal Of High Performance Computing Applications*, 15:56-74



Not all block inverses need to be approximated with a full multigrid cycle:

- Due to Schur complement calculation, good approximation of one matrix block is already available
- Using this information for smoothing results in the following SPAI smoother⁴:

$$x^{k+1} = x^k - \hat{A}(Ax^k - b)$$

with \hat{A} being a sparse approximate inverse

Solve "Schur complement" equation with a conventional AMG method:

- Standard relaxation methods don't converge due to non-diagonal dominance
- Polynomial smoothers like the Chebyshev iteration provide decent results

⁴Bröker O. and Grote, M. J. (2002): "Sparse approximate inverse smoothers for geometric and algebraic multigrid", *Applied Numerical Mathematics*, 41:61-80



Settings

Discretization

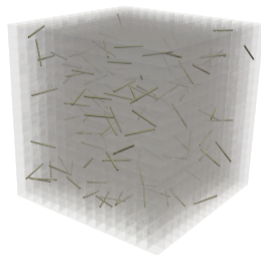
Solid DOFs: 12288
Beam DOFs: 1860
procs: 6

Solver

Newton convergence: 10^{-6} (rel)
GMRES convergence: 10^{-8} (rel)

Material Parameters

Solid: $E_S = 100 \frac{N}{m^2}$, $\nu_S = 0.3$
hyperelastic Saint Venant-Kirchhoff model
Beam: $E_B = 1000 \frac{N}{m^2}$, $\nu_B = 0.0$
torsion-free Kirchhoff-Love model
Penalty: $p = 1000 \frac{N}{m}$



- Minimal working example to investigate the influence of the sparse inverse approximation to the block smoothing schemes
- Sub-solves are done with a direct method



Block LU

τ	$1e^{-1}$	$1e^{-2}$	$1e^{-3}$	$1e^{-4}$	$1e^{-5}$	$1e^{-6}$
$J(A^0)$	184	184	184	184	184	184
$J(A^1)$	171	74	23	21	21	21
$J(A^2)$	193	102	14	9	9	8
$J(A^3)$	174	15	15	6	3	2

- Shows the averaged iterations of the linear solver in the first newton step
- Sparsity pattern level on the left side and the threshold value for pre- and post filtration on the top
 - ⇒ $J(A^0)$ is equivalent to the matrix diagonal $J(diag(A))$
 - ⇒ $J(A^1)$ resembles the sparsity pattern $J(A)$
 - ⇒ The patterns $J(A^2)$ and $J(A^3)$ are the respective combinations on level 2 and 3



SIMPLE ($s = 3, \omega = 0.7$)

τ	$1e^{-1}$	$1e^{-2}$	$1e^{-3}$	$1e^{-4}$	$1e^{-5}$	$1e^{-6}$
$J(A^0)$	-	-	-	-	-	-
$J(A^1)$	-	-	-	369	68	48
$J(A^2)$	-	-	320	11	11	11
$J(A^3)$	-	-	-	7	5	4

value "-" means no convergence

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 - ⇒ $J(A^0)$ is equivalent to the matrix diagonal $J(diag(A))$
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Uzawa ($s = 3, \omega = 0.7$)

τ	$1e^{-1}$	$1e^{-2}$	$1e^{-3}$	$1e^{-4}$	$1e^{-5}$	$1e^{-6}$
$J(A^0)$	-	-	-	-	-	-
$J(A^1)$	-	-	-	287	47	38
$J(A^2)$	-	-	268	11	11	11
$J(A^3)$	-	-	-	7	5	4

value "-" means no convergence

- Shows the averaged iterations of the linear solver in the first newton step
- Sparsity pattern level on the left side and the threshold value for pre- and post filtration on the top
 - ⇒ $J(A^0)$ is equivalent to the matrix diagonal $J(diag(A))$
 - ⇒ $J(A^1)$ resembles the sparsity pattern $J(A)$
 - ⇒ The patterns $J(A^2)$ and $J(A^3)$ are the respective combinations on level 2 and 3



Settings

Discretization

Solid DOFs: 5376
Beam DOFs: 1686
procs: 6

Solver

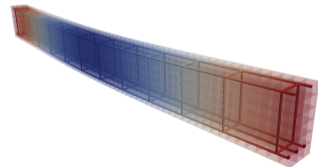
Newton convergence: 10^{-6} (rel)
BiCGSTAB convergence: 10^{-8} (rel)

Material Parameters

Solid: $E_S = 30 \frac{N}{m^2}$, $\nu_S = 0.3$
hyperelastic Saint Venant-Kirchhoff model
Beam: $E_B = 210 \frac{N}{m^2}$, $\nu_B = 0.0$
torsion-free Kirchhoff-Love model
Penalty: $p = 1000 \frac{N}{m}$



Four-point bending test under static loading⁵



⁵Braml, T.; Wimmer, J. and Varabei, Y. (2022): "Erfordernisse an die Datenaufnahme und -verarbeitung zur Erzeugung von intelligenten Digitalen Zwillingen", *Innsbrucker Bautage 2022 (eds Berger, J.) (Studia, 2022)*, 31-49



Settings

Discretization

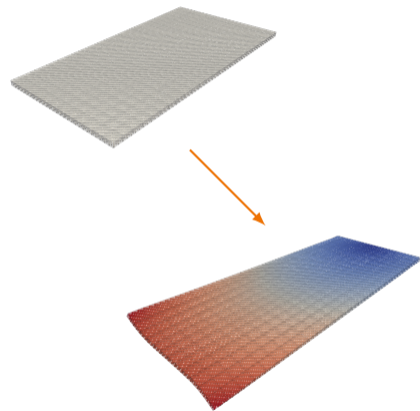
Solid DOFs: 1950
Beam DOFs: 10992
procs: 6

Solver

Newton convergence: 10^{-6} (rel)
BiCGSTAB convergence: 10^{-8} (rel)

Material Parameters

Solid: $E_S = 10 \frac{N}{m^2}$, $\nu_S = 0.3$
hyperelastic Saint Venant-Kirchhoff model
Beam: $E_B = 1000 \frac{N}{m^2}$, $\nu_B = 0.0$
torsion-free Kirchhoff-Love model
Penalty: $p = 1000 \frac{N}{m}$

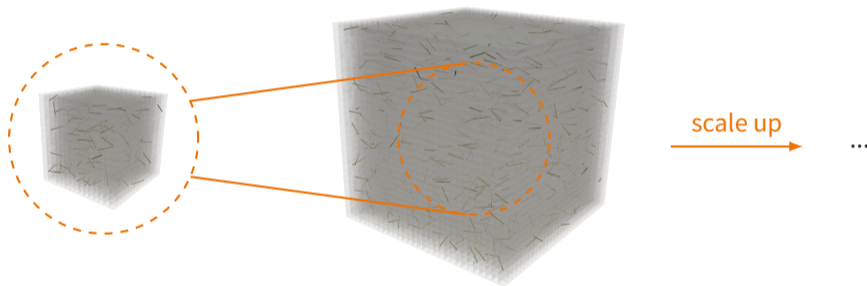


Deformation of the plate due to tensile load

⁶Steinbrecher, I.; Mayr, M.; Grill, M. J.; Kremheller, J.; Meier, C. and Popp, A. (2020): "A mortar-type finite element approach for embedding 1D beams into 3D solid volumes", *Computational Mechanics*, 66:1377-1398



Weak scaling study: Cube filled with randomly placed and oriented fibers.



1 x 1 x 1 domain

- ~ 25.000 Dofs
- 1 Processor

2 x 2 x 2 subdomains

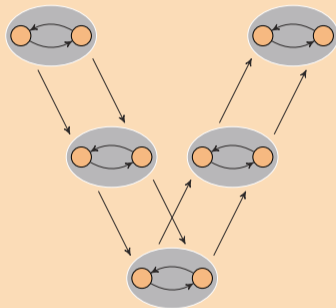
- ~ 200.000 Dofs
- 8 Processors

$n \times n \times n$ subdomains

- ~ ? Dofs
- n^3 Processors



AMG(BlockMethod)



- Consider coupling constraints on all levels
- Assembly of the beam DOFs nullspace specific to beam formulation

- For now only considered torsion-free Kirchhoff–Love beam elements:
 - ⇒ Sufficient for a broad range of applications
 - ⇒ Restriction to straight center line in reference configuration
- Extend to other beam formulations in the near future.



Collaborators:

- Matthias Mayr
- Alexander Popp
- Ivo Steinbrecher

References:

Open-source implementation will be available in
TrilinosMueLu: <https://trilinos.github.io/muelu.html>



Contact:

- max.firnbach@unibw.de
- <https://www.unibw.de/imcs-en>