#### Abstract

## "Improving the iterative methods in TNO DIANA using physical properties of the underlying model"

Alex Sangers - December 10, 2013 at 16:00 in EEMCS Room 1.2

DIANA is a multi-purpose finite element software package that is dedicated to e.g. structural and geotechnical engineering problems. The solution of one or more systems of linear equations is a computational intensive part of a finite element analysis. For this purpose a number of direct and iterative methods are available in DIANA.

As the demand for larger finite element analysis grows every year, so lead the corresponding models to large linear systems. Iterative methods have proved to be effective to solve these systems.

The purpose of this research is to find out how the iterative methods of DIANA can be improved. One technique considered is deflation, based on the physical properties of the underlying problem. Another technique is scaling the system based on the type of degree of freedom, such as translation, rotation or pressure.





Iterative methods at DIANA Improving the iterative methods in TNO DIANA using physical properties of the underlying model.

**Alex Sangers** 

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December 10, 2013





#### Content

Finite Element Analysis at DIANA

Iterative solution methods at DIANA

Other solution techniques at DIANA

Enhancements

Illustrative results

Challenges



Some relevant quantities:

- $\boldsymbol{u}$  displacements
- $\varepsilon$  strain
- $\sigma$  stress



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- $\boldsymbol{u}$  displacements
- $\varepsilon$  strain
- $\sigma$  stress

In case of linear elastic behavior:

$$\varepsilon = B_m u,$$

with  $B_m$  the differential matrix,

$$\sigma = D_m \varepsilon,$$

with  $D_m$  the elasticity matrix.



 $\boldsymbol{K}$  and  $\boldsymbol{f}$  are assembled by

$$K^{e_m} = \int_{e_m} B_m^T D_m B_m \ dV, \qquad f^{e_m} = \int_{e_m} \sum_i f_i^{e_m} \ dV$$



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 $\label{eq:Result: Ku = f, K \in \mathbb{R}^{n \times n}, f \in \mathbb{R}^n.$ 



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#### Computationally intensive part!



Direct and iterative methods.



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#### **Direct methods:**

- LU or Cholesky decomposition
- Pardiso (parallel LU)



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#### Iterative methods:

- Conjugate Gradient Method
- Generalized Minimal Residual Method



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- Generalized Minimal Residual Method

Properties of iterative methods:

- Require less memory
- In general less robust
- Effective for important classes of problems



## Iterative solution methods available at DIANA

#### Symmetric case: Conjugate Gradient (CG)

- Lanczos-based algorithm
- Strategy: orthogonalizes the residuals
- Optimality
- Short-recurrence



# Iterative solution methods available at DIANA

#### Symmetric case: Conjugate Gradient (CG)

- Lanczos-based algorithm
- Strategy: orthogonalizes the residuals
- Optimality
- Short-recurrence

#### Nonsymmetric case:

(Restarted) Generalized Minimal Residual ( GMRES(s) )

- Arnoldi-based algorithm
- Strategy: minimizes the residuals
- Optimality (if no restart)
- Long-recurrence



#### Preconditioning

The convergence of iterative methods depend on eigenvalues and eigenvectors.

For SPD matrix K holds for the  $m\mbox{-th}$  CG iteration:

$$||u - u_m||_K \le 2 \left[\frac{\sqrt{\lambda_{\max}/\lambda_{\min}} - 1}{\sqrt{\lambda_{\max}/\lambda_{\min}} + 1}\right]^m ||u - u_0||_K$$



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 $\label{eq:preconditioning} {\rm R} u = f \ \Rightarrow \ P^{-1} {\rm K} u = P^{-1} f {\rm ,}$ 

where:

$$\blacktriangleright P \approx K \Rightarrow P^{-1}K \approx I.$$

• Px = y is easy to solve.

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## Substructuring and Domain decomposition



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#### Substructuring

$$K \sim \begin{pmatrix} A_1 & & B_1 \\ & \ddots & & \vdots \\ & & A_{n_s} & B_{n_s} \\ B_1^T & \dots & B_{n_s}^T & C \end{pmatrix}$$

- No parallel implementation
- Partitioning the elements
- No overlap in partitions
- One preconditioner



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#### Domain decomposition

$$K = \sum_{i=1}^{n_d} L_i^T K_i R_i$$

- No parallel implementation
- Partitioning the elements
- No overlap in partitions
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- Parallel implementation
- Partitioning the nodes
- Overlap allowed in partitions
- Dual preconditioner

#### Enhancements

#### **Required improvements:**

- Jumps in material properties
- Multiple types of degrees of freedom
- Interface elements: 'coupling' elements
- Mixture elements: pressure-translation elements
- Nonlinear loops



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#### **Required improvements:**

- Jumps in material properties
- Multiple types of degrees of freedom
- Interface elements: 'coupling' elements
- Mixture elements: pressure-translation elements
- Nonlinear loops

#### **Techniques:**

- Deflation
- Scaling
- IDR(s)



Define

$$\begin{split} \Pi^{\in} &= I - Z(Y^T K Z)^{-1} Y^T K, \\ \Pi^{\perp} &= I - K Z(Y^T K Z)^{-1} Y^T, \end{split}$$

so that  $\Pi^{\perp}K = K\Pi^{\in}$ .



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$$u = u^{\in} + u^{\perp}$$
  
=  $(I - \Pi^{\in})u + \Pi^{\in}u.$ 



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**T**UDelft

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#### Subdomain deflation:

$$Z_{ij} = \left\{ \begin{array}{ll} 1 & \text{if } i \in G_j, \\ 0 & \text{otherwise.} \end{array} \right.$$



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Rigid body mode deflation:
Z is approximate null space of element matrices corresponding to 'near-rigid bodies'.



### Rigid body mode deflation: Example



#### Figure: Stiff sphere in block.

Young's modulus 
$$E(\underline{x}) = \begin{cases} 1 & \text{if } \underline{x} \in \mathsf{block}, \\ 10^6 & \text{if } \underline{x} \in \mathsf{sphere}. \end{cases}$$



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Figure: Stiff sphere in block.

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## Scaling

Example:

Translation degrees of freedom: $\mathcal{O}(t)$ Rotation degrees of freedom: $\mathcal{O}(r)$ Pressure degrees of freedom: $\mathcal{O}(p)$ 



## Scaling

Example:

Right preconditioning:

$$KP^{-1}x = f, \quad u = P^{-1}x,$$

with  $P = \operatorname{diag}(\{t, r, p\})$ .



## IDR(s)

#### Nonsymmetric systems: No 'best' algorithm.

IDR(s) forces residuals  $r_n$  in subspace  $G_j$  of decreasing dimension. Some freedom in algorithm remains.

GMRES(s)	IDR(s)
Long recurrences	Short recurrences
Optimal if no restart	Not optimal



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- Large systems of equations
- Ill-conditioned problems



#### Rigid body mode deflation so far...





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## Rigid body mode deflation so far...



Analogue behavior for three stiff blocks in a block.





- Identification of rigid bodies
  - Young's modulus of materials
  - Interface elements
  - Spring elements
  - (Shell elements)
  - (Contact elements)



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  - Combination with other preconditioners



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- Scaling
  - Identifying orders of magnitude (units, expected solution)
  - Combination with other preconditioners
- Nonlinear iteration loop
  - When to reuse information?
  - How to reuse information (rigid bodies, Ritz vectors, etc.)?



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