

# CEMRACS Project Elasto $\Phi$

Boundary integral methods for elasticity around a crack network

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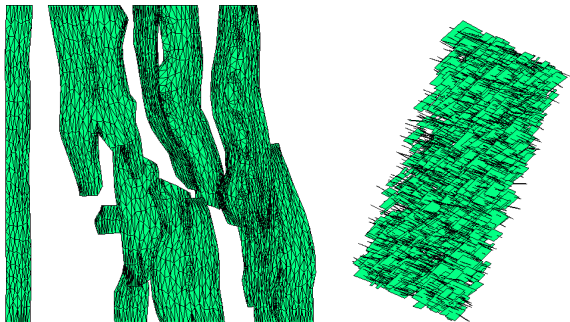


*Alpes*



# The Elasto $\Phi$ project: the IFPEN problem

Elastostatic problem in **crack networks** of 2 types: geological *fault* network and discrete *fracture* network



Boundary *integral equation* posed at the surface of cracks  
 $\Rightarrow$  **dense matrix**  $A \in \mathbb{R}^{n \times n} \Rightarrow \mathcal{O}(n^2)$  for matrix-vector product.

IFPEN heuristic approach to sparsify  $A$  gives large error (16%–40%)

# The Elasto $\Phi$ project

Many refined *complexity reduction* techniques in current literature on boundary integral equation.

Two ingredients in the approach we considered:

- Adaptative Cross Approximation (**ACA**),
- Hierarchical Matrices (**HM**).

Challenge: *strongly irregular geometry!*

[M. Bebendorf. Hierarchical matrices: A Means to Efficiently Solve Elliptic Boundary Value Problems, *Lecture Notes in Computational Science and Engineering*, 2008]

[S. Rjasanow, O. Steinbach. The fast solution of boundary integral equations. *Mathematical and Analytical Techniques with Applications to Engineering*, 2007]

[W. Hackbusch. Hierarchical Matrices: Algorithms and Analysis, *Springer Series in Computational Mathematics*, 2016]

# Adaptative Cross Approximation (ACA)

The idea of the Singular Value Decomposition (SVD)

Suppose that  $A \in \mathbb{R}^{n \times n}$  is of **low rank**, i.e.

$$A = \sum_{j=1}^k \mathbf{u}_j \cdot \mathbf{v}_j^T \quad \text{with} \quad k \leq n/2.$$

$\Rightarrow$   **$2kn$**  operations for matrix-vector product.

**SVD** actually gives the following decomposition:

$$A = \sum_{j=1}^n \sigma_j \mathbf{u}_j \cdot \mathbf{v}_j^T \quad \text{where } \{\sigma_j^2\}_{j=1 \dots n} \text{ are the eigenvalues of } A^T A.$$

If the  $\sigma_j$  decrease fast, *truncated SVD* is a good approximation of  $A$ !

But it costs  $\mathcal{O}(n^3)$  ...

# Adaptative Cross approximation (ACA)

An approximation of the Singular Value Decomposition (SVD)

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## Algorithm 1 Partially Pivoted ACA

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Initialize  $j_*$   $r = 0$

**while**(stopping criterion not satisfied){

$$\mathbf{w} = A(j_*, :)^T - \sum_{\ell=1}^r \mathbf{u}_\ell(j_*) \mathbf{v}_\ell$$

$$k_* = \operatorname{argmax}_{k=1\dots n} |\mathbf{w}(k)|$$

$$w_* = \mathbf{w}(k_*)$$

**if**( $w_* \neq 0$ ){

$$\mathbf{v}_{r+1} = \mathbf{w}$$

$$\mathbf{w} = A(:, k_*) - \sum_{\ell=1}^r \mathbf{v}_\ell(k_*) \mathbf{u}_\ell$$

$$\mathbf{u}_{r+1} = w_*^{-1} \mathbf{w}$$

$$j_* = \operatorname{argmax}_{j=1\dots n} |\mathbf{w}(j)|$$

$$r = r + 1$$

}

**else**{terminate algorithm}

}

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Advantages:

- No need to assemble the entire matrix
- Cost and storage in  $\mathcal{O}(n \log n)$

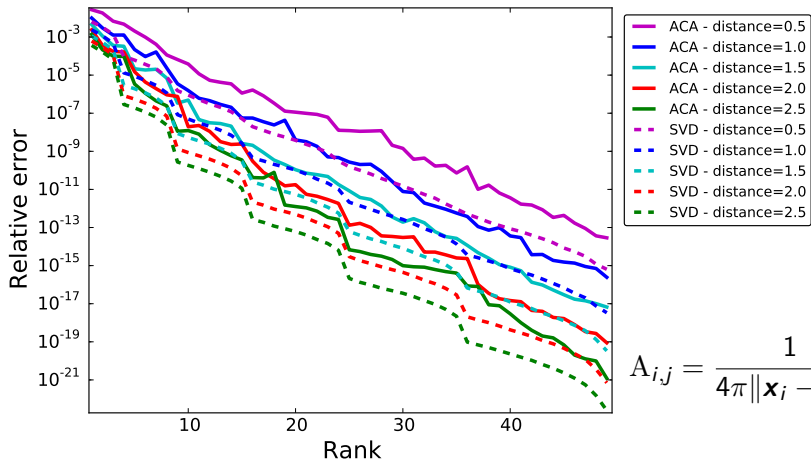
Remark:

- Function computing the coefficients on the fly necessary to be more efficient in practice

# Adaptative Cross Approximation (ACA)

## Comparison between SVD and ACA

Compression of the interaction matrix between *two clusters*  $\{\mathbf{x}_i\}$  and  $\{\mathbf{y}_j\}$



$$A_{i,j} = \frac{1}{4\pi \|\mathbf{x}_i - \mathbf{y}_j\|}$$

# Adaptative Cross Approximation (ACA)

In practice in our application

The matrix comes from the discretization of a boundary integral equation

$$A_{j,k} := \int_{\tau \times \tau'} \mathcal{G}(\mathbf{x} - \mathbf{y}) \psi_j(\mathbf{x}) \psi_k(\mathbf{y}) d\sigma(\mathbf{x}) d\sigma(\mathbf{y}), \quad j, k = 1 \dots n.$$

$\mathcal{G}$  is an *integral kernel* with these properties:

- it is *singular* for  $\mathbf{x} = \mathbf{y}$ , i.e. if  $\tau \cap \tau' \neq \emptyset$ ,
- it is *regularizing* if  $\tau$  and  $\tau'$  are **distant** from each other.

⇒ ACA is applicable to **admissible blocks** of A

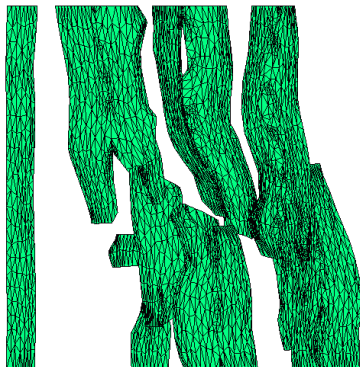
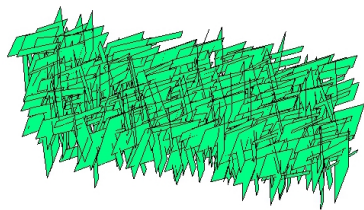
⇒ Hierarchical Matrices (HM)

# Hierarchical matrices (HM)

An example of cluster tree

1. First step to build the blocks of the **hierarchical matrix**:  
building a *tree* of **clusters of points**.

The unknowns correspond to mesh element barycenters.



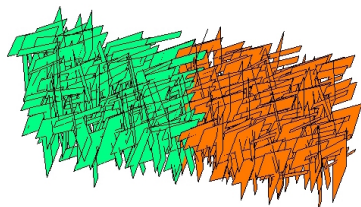


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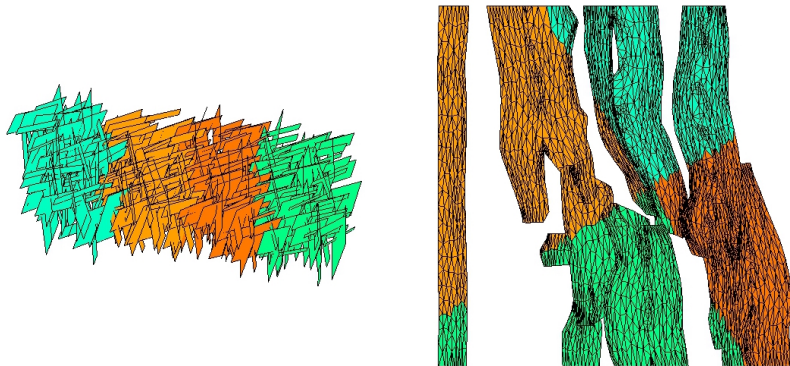


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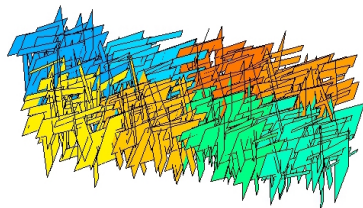


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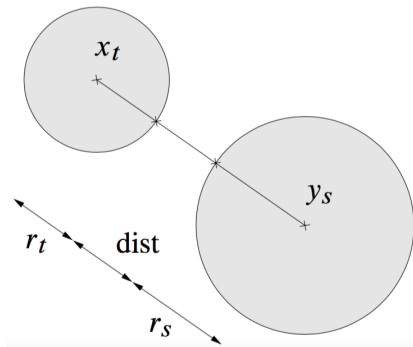
# Hierarchical matrices (HM)

## Admissible blocks

Interactions between nodes of the cluster tree  $\Leftrightarrow$  sub-blocks of  $A$ .

2. Second step: checking *recursively* the admissibility of the blocks with the following **admissibility condition** on the associated clusters:

$$\min(\text{diam}(B_t), \text{diam}(B_s)) < \eta \text{dist}(B_t, B_s)$$



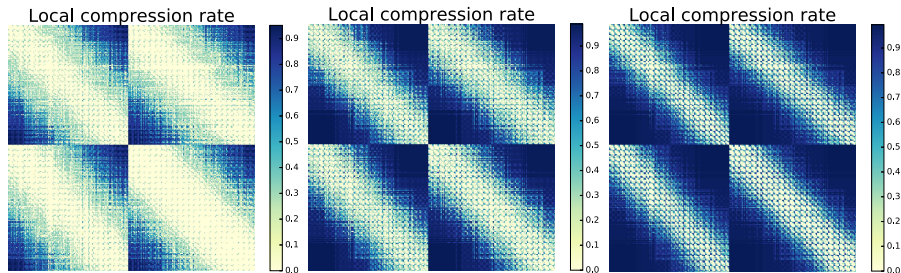
$\Rightarrow$  apply ACA to the admissible blocks.

# Results

C++ implementation, our source code is available on GitHub at:

<https://github.com/xclaeys/ElastoPhi>

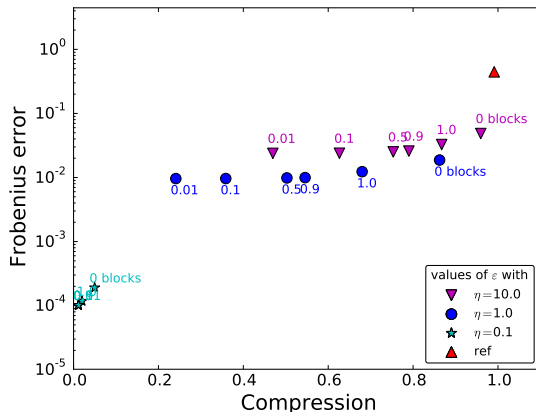
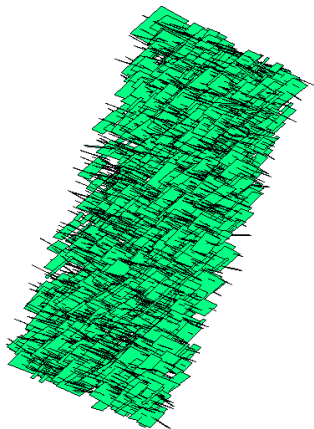
Varying the parameters of the algorithm:



- Remark: a block is not necessarily a connected part of the matrix.

# Results

Network of  $N = 1994$  fractures: size  $A = 3N \times 3N$



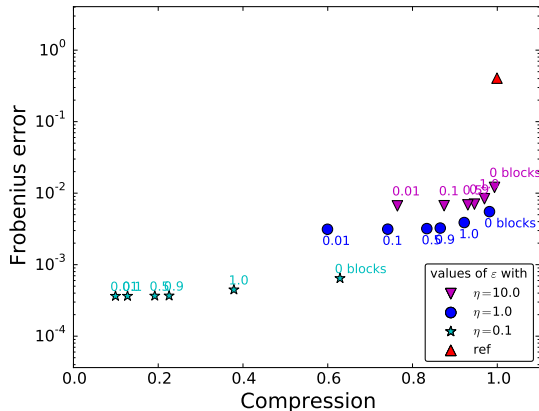
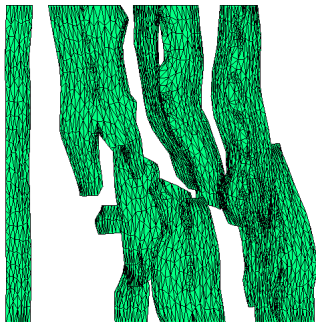
IFPEN sparse matrix: compression rate = 0.99, error = 45%

H matrix, zero blocks and  $\eta = 1$ : compression rate = 0.86, error = 2%

HM-ACA matrix,  $\varepsilon = 1$  and  $\eta = 1$ : compression rate = 0.68, error = 1%

# Results

Network of **faults** with  $N = 5364$  mesh triangles: size  $A = 3N \times 3N$



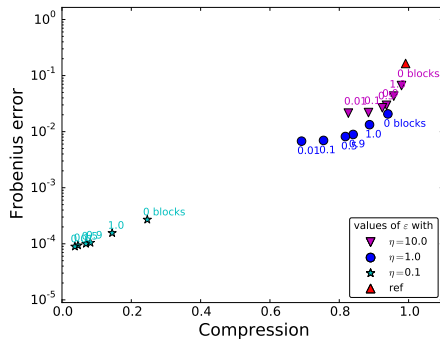
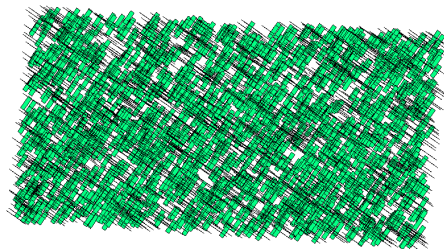
IFPEN sparse matrix: compression rate = 0.999, error = **41%**

H matrix, zero blocks and  $\eta = 1$ : compression rate = 0.98, error = 0.55%

HM-ACA matrix,  $\varepsilon = 1$  and  $\eta = 1$ : compression rate = 0.92, error = **0.38%**

# Results

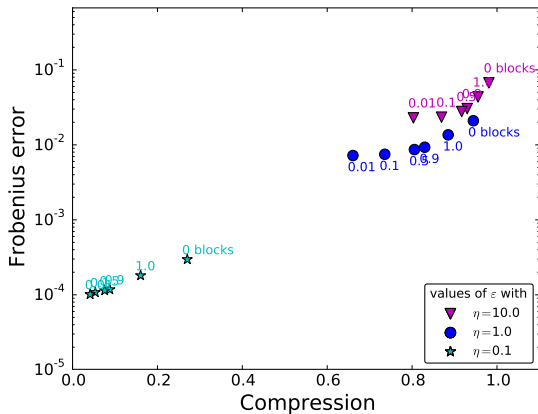
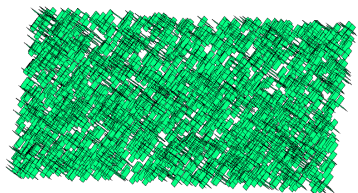
Network of  $N = 3600$  fractures: size  $A = 3N \times 3N$





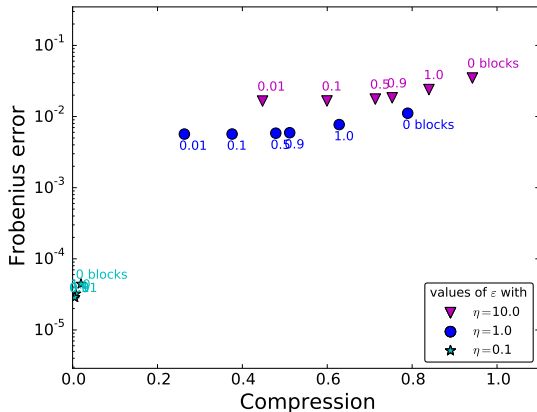
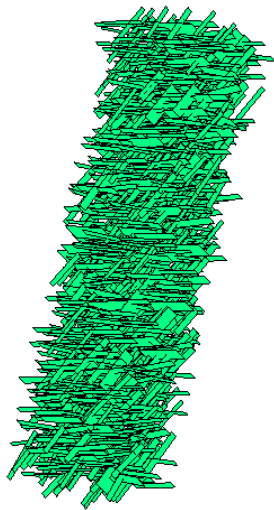
# Results

Network of  $N = 2700$  fractures: size  $A = 3N \times 3N$



# Results

Network of  $N = 1363$  fractures: size  $A = 3N \times 3N$



# Conclusion and outlook

- We obtained approximation errors suited to IFPEN applications with high compression rates,
- to treat large industrial cases, we have to compute *only the needed coefficients* of the matrix *on the fly*, in order to really exploit the low complexity of ACA  
(not possible during CEMRACS for confidentiality reasons),
- design a *new admissibility condition* to take in account the *direction* of the fractures,
- *parallelization* of the code.

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Thank you for your attention!