

# High performance numerical algorithms and tools

HiePACS - Inria Bordeaux Sud-Ouest

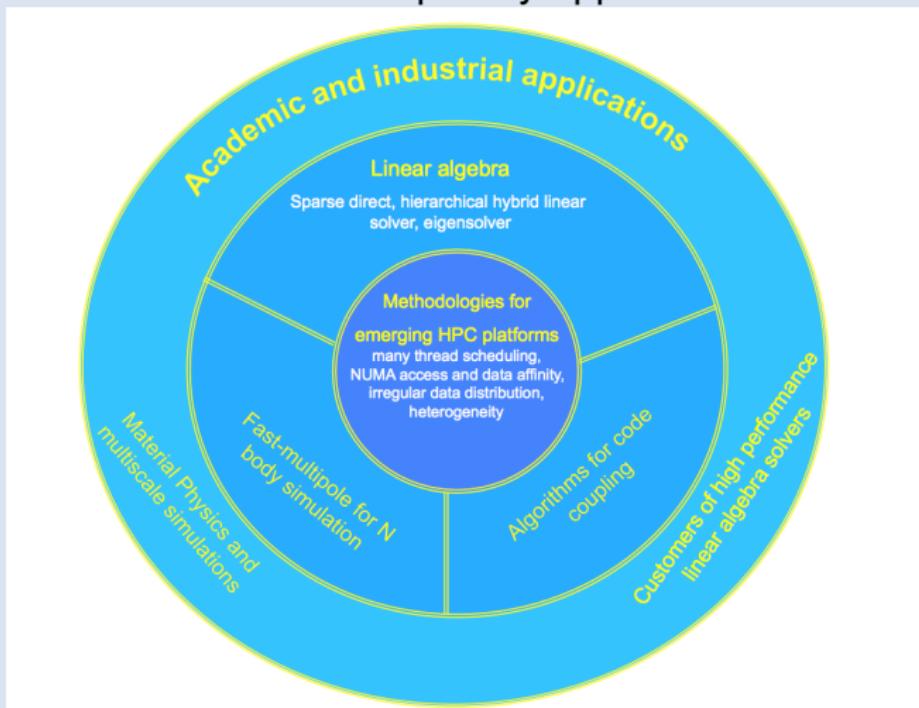
First Brazil-France workshop  
Petropolis, September 17-19, 2012



# HiePACS onion scientific structure

Objectives: contribute to the effort towards Peta/Exascale computing

A multidisciplinary approach



# Outline

1. Fast Multipole Method on a Runtime System
2. Parallel sparse hybrid linear solver
3. Parallel geometric multigrid
4. Concluding remarks

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# Fast Multipole

Joint work with (FAST-LA associated team)

Éric DARVE (Stanford University)

Toru TAKAHASHI (Nagoya University)

# Fast Multipole Background (1/3)

## Objectives

Compute

$$f_i = \sum_{j=1}^N P(x_i, y_j) w_j \quad \text{for } i = 1, \dots, M$$

$P$  is the dense matrix (kernel of a Green's function, that decays with distance).

## Main decomposition idea

$$f_i = f_i^{near} + f_i^{far}$$

where  $f_i^{far}$  approximated by analytical expansions

1. Development: Taylor, spherical harmonic
2. Interpolation (black-box) [Darve & Fong, JCP, 2009]

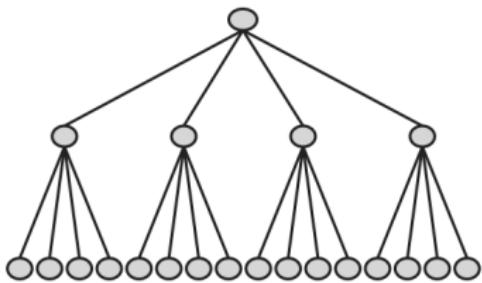
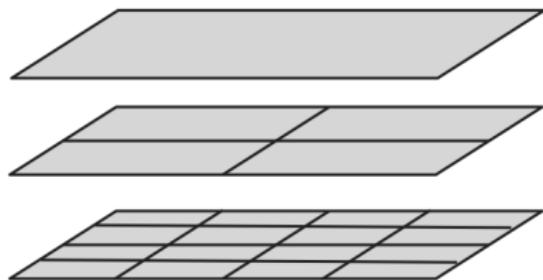
# Fast Multipole Method (2/3)

Far field calculation: a shortcut



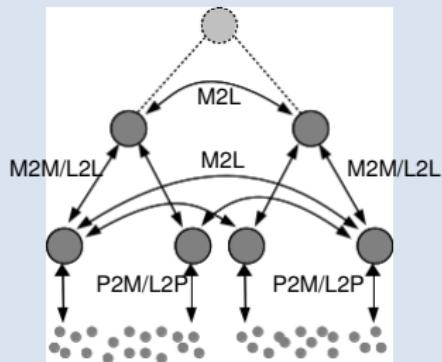
# Fast Multipole Method (2/3)

## Far field calculation: a shortcut



# Fast Multipole Method (3/3)

## Simplified FMM tree

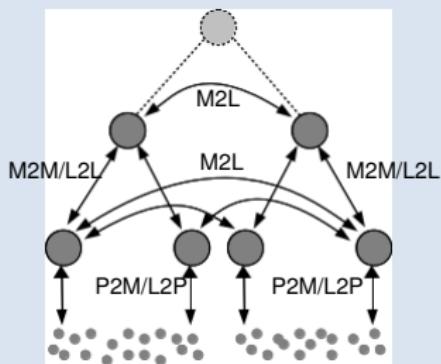


## FMM main operators

- ★ P2P : Particule to Particule (near field)
- ★ P2M : Particule to Multipole (up)
- ★ M2M : Multipole to Multipole (up)
- ★ M2L : Multipole to Local
- ★ L2L : Local to Local (down)
- ★ L2P : Local to Particule (down)

# Fast Multipole Method (3/3)

## Simplified FMM tree



## FMM main operators

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# Implementation : three-layer paradigm

High-level algorithm

FMM

Runtime System

STARPU

Device kernels

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Device kernels

CPU core

All 6 kernels

FC2 (optimized)

FC2L (non optimized)

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GPU

- ★ P2P (optimized)
- ★ M2L (non optimized)

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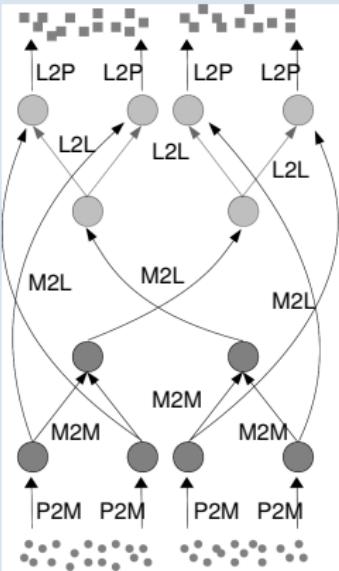
- ★ P2P (optimized)
- ★ M2L (non optimized)

# StarPU runtime system

- ★ Developed by Inria Runtime team;
- ★ Ensures data coherency:
  - ▶ Modified Shared Invalid (MSI) protocol;
- ★ Productive programming paradigm:
  - ▶ Implicit task dependency
- ★ Unified runtime system
  - ▶ SMP/multicore, Nvidia GPUs, OpenCL devices, Cell processors;
  - ▶ Distributed memory;
  - ▶ Soon: Intel SCC and MIC.

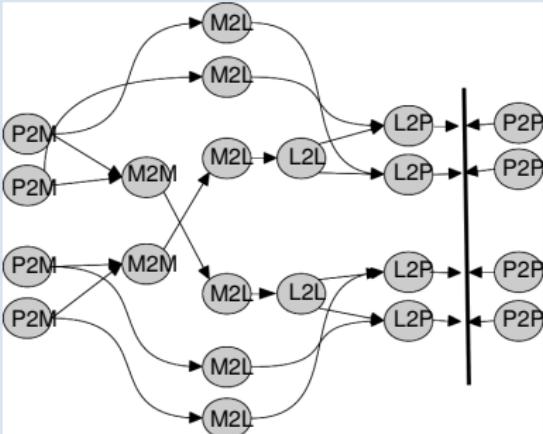
# FMM task flow

## Mirrored tree



- ★ Vertex: data
- ★ Edge: task

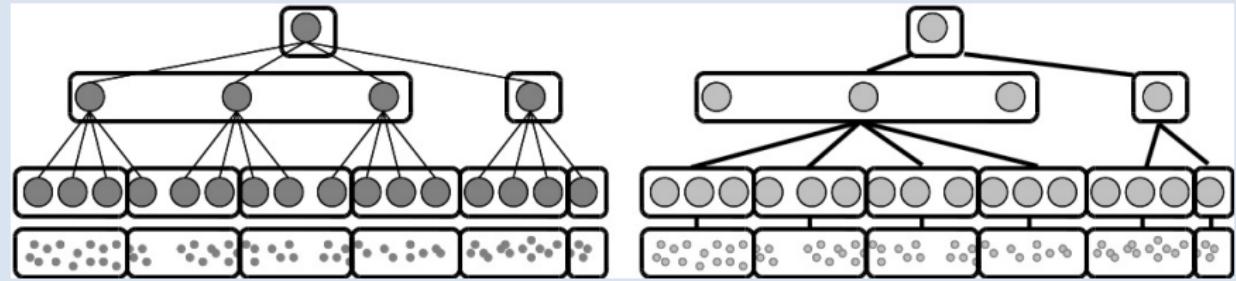
## Task flow: far field | near field



- ★ Vertex: task
- ★ Edge: task dependency

# Granularity

Gather leaves to coarsen the DAG



# Set up

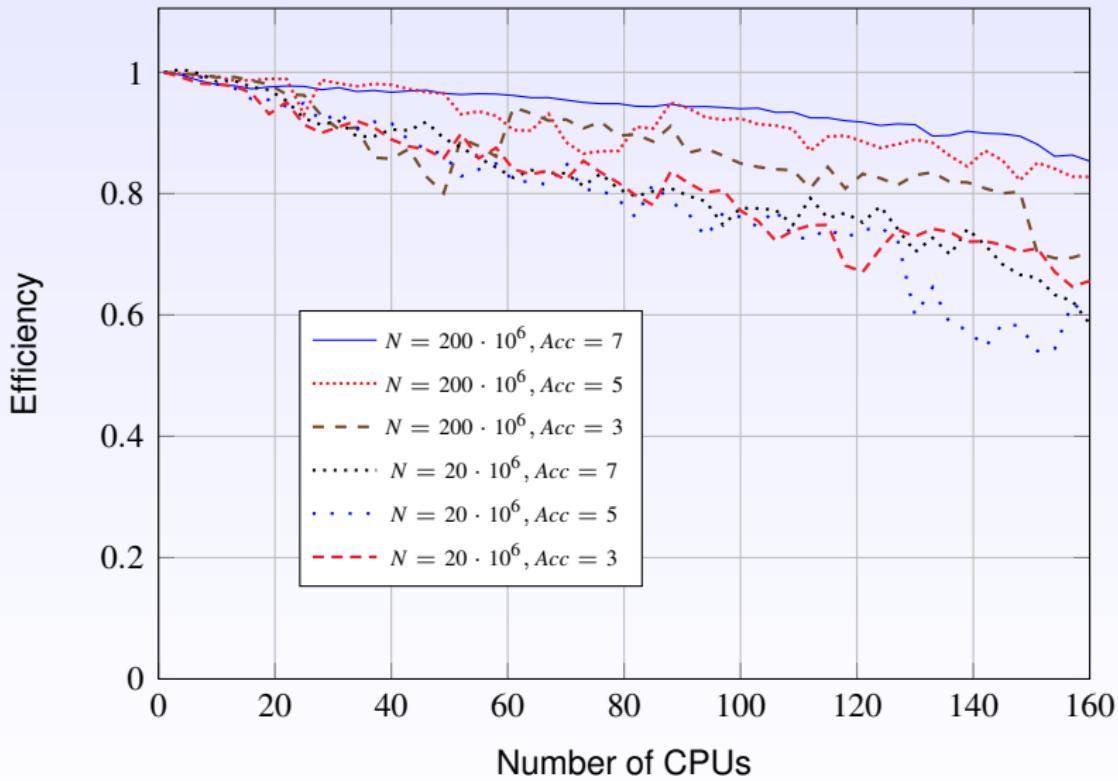
## 160 cores machine (SGI Altix UV 100)

- ★ twenty octa-core Intel Xeon E7-8837 processors
- ★ 2.67 GHz;
- ★ ccNUMA;

## Parallel Efficiency ( $e_p$ )

$$e_p = \frac{t_1}{p \times t_p},$$

## 160 cores machine - Performance



# Nehalem-Fermi machine

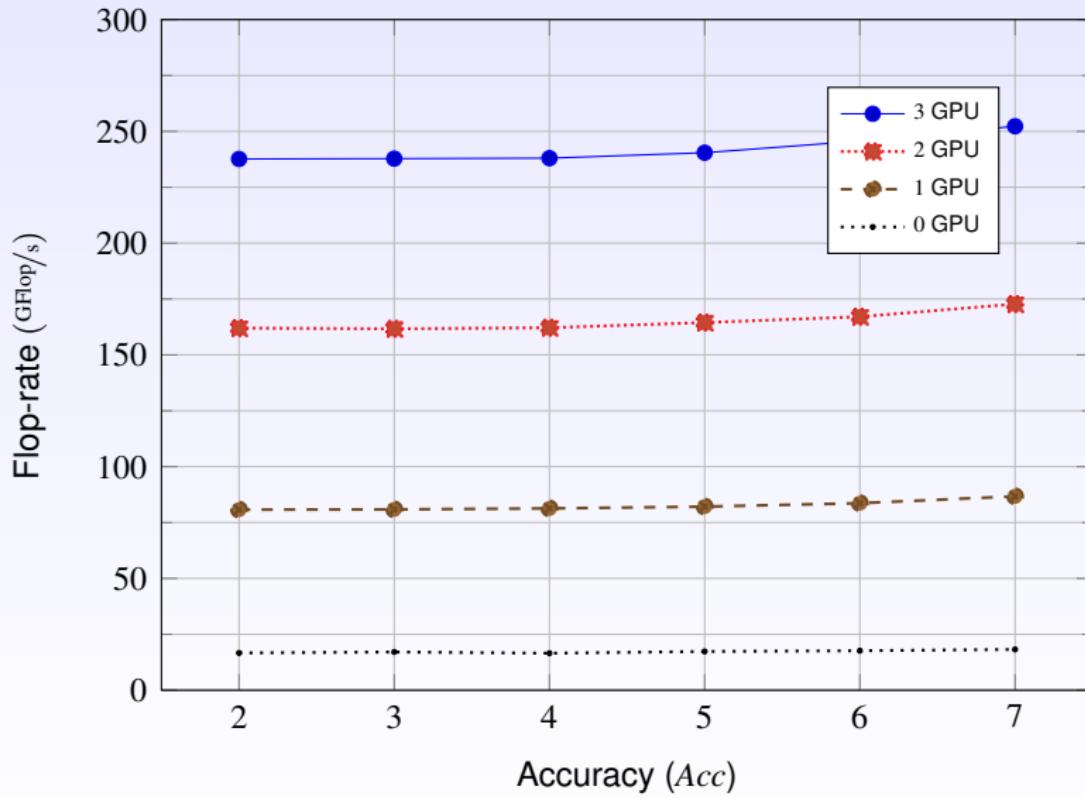
## Host (12 cores)

- ★ dual-socket hexa-core Intel X5650 Nehalem processors;
- ★ 2.67 GHz;
- ★ ccNUMA.

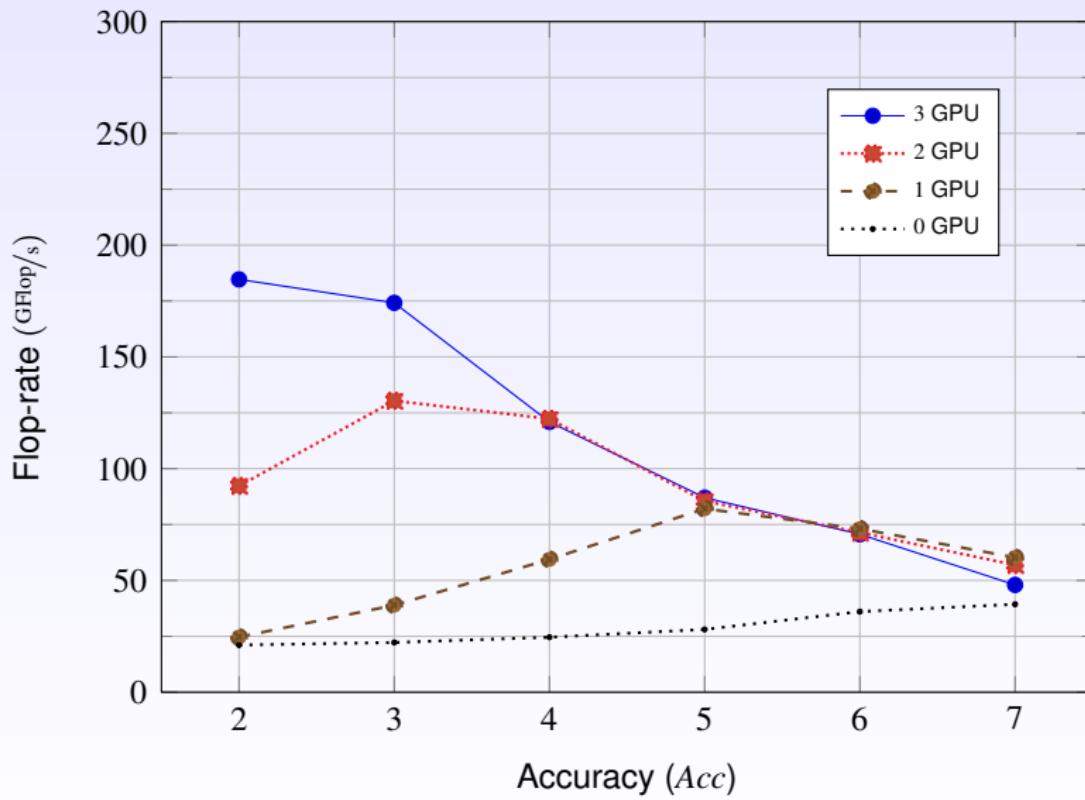
## Devices (3 GPUs)

- ★ Nvidia Fermi M2070
- ★ 6 GB;
- ★ 16x PCI bus to the host.

## Non Uniform Distribution - Cube - h=7



## Non Uniform Distribution - Cube - h=8



# Conclusion

## Conclusion

- ★ Performance portability across architectures;
- ★ Matrices Over Runtime Systems @ Exascale (MORSE):
  - ▶ Dense linear algebra (Magma);
  - ▶ Sparse direct solver (PaStiX);
  - ▶ FMM (ScalFMM) ;
- ★ Dominant far field:
  - ▶ Need to improve M2L kernel (on-going).

## Future work

- ★ Distributed memory;
- ★ All 6 kernels on GPU;
- ★ AMD Tahiti (OpenCL) and Intel MIC accelerators;
- ★ DAGuE runtime system.

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# Hybrid solver: Motivations

Goal: solving  $\mathcal{A}x = b$ , where  $\mathcal{A}$  is large and sparse



## Usual trades off

### Direct

- ★ Robust/prescribed accurate for general problems
- ★ BLAS-3 based implementations
- ★ Memory/CPU prohibitive for large 3D problems
- ★ Limited weak scalability

### Iterative

- ★ Problem dependent efficiency / monitored accuracy
- ★ Sparse computational kernels
- ★ Less memory requirements and possibly faster
- ★ Possible high weak scalability

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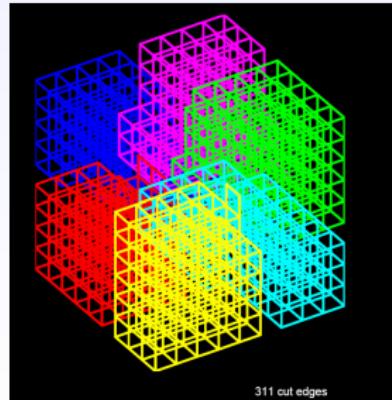
# Governing Ideas in Hybrid Linear Solvers

Develop robust scalable parallel hybrid direct/iterative linear solvers

- ★ Exploit the efficiency and robustness of the sparse direct solvers
- ★ Develop robust parallel preconditioners for iterative solvers
- ★ Take advantage of the natural scalable parallel implementation of iterative solvers

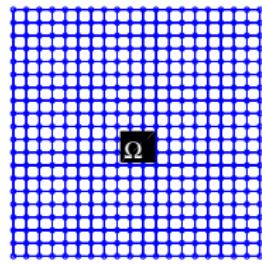
## Domain Decomposition (DD)

- ★ Natural approach for PDE's
- ★ Extend to general sparse matrices
- ★ Partition the problem into subdomains, subgraphs
- ★ Use a direct solver on the subdomains
- ★ Robust preconditioned iterative solver

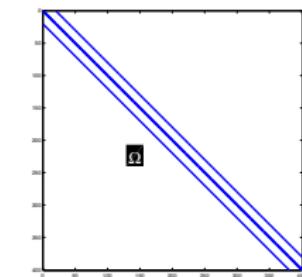


# General partitioning of sparse matrix

Mesh view



Matrix view



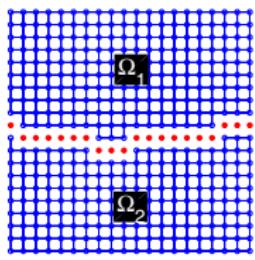
Tree view



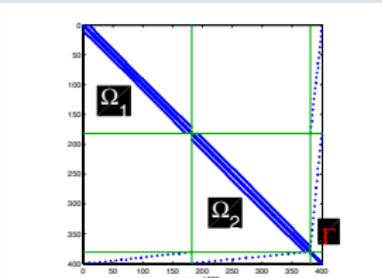
- ★ Partitioning a matrix using algebraic algorithm based on the adjacency graph of  $\mathcal{A}$
- ★ 2 ways partitioning:
  - Computing an edge separator then finding the best vertex separator
  - Computing a vertex separator

# General partitioning of sparse matrix

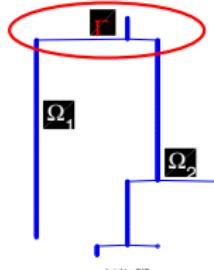
Mesh view



Matrix view



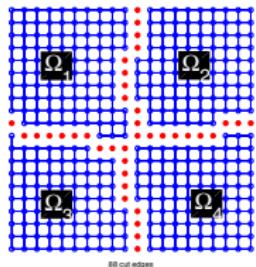
Tree view



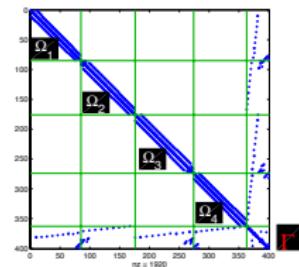
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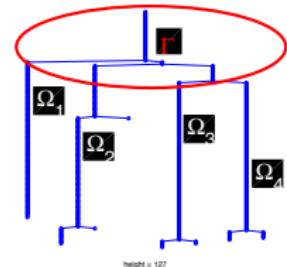
## Mesh view



## Matrix view



## Tree view



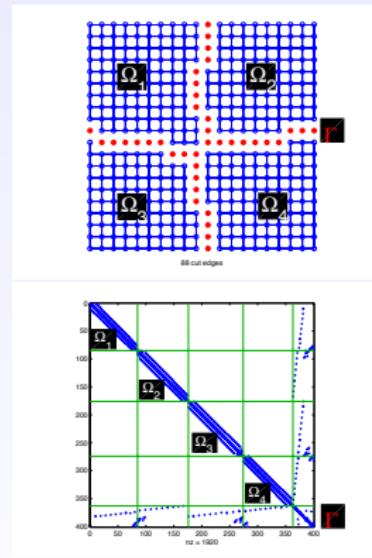
## Global algebraic view

- ★ Global hybrid decomposition:

$$\mathcal{A} = \begin{pmatrix} \mathcal{A}_{\mathcal{I}\mathcal{I}} & \mathcal{A}_{\mathcal{I}\Gamma} \\ \mathcal{A}_{\Gamma\mathcal{I}} & \mathcal{A}_{\Gamma\Gamma} \end{pmatrix}$$

- ★ Global Schur complement:

$$\mathcal{S} = \mathcal{A}_{\Gamma\Gamma} - \mathcal{A}_{\Gamma\mathcal{I}}\mathcal{A}_{\mathcal{I}\mathcal{I}}^{-1}\mathcal{A}_{\mathcal{I}\Gamma}$$



## Local algebraic view

- ★ Local hybrid decomposition:

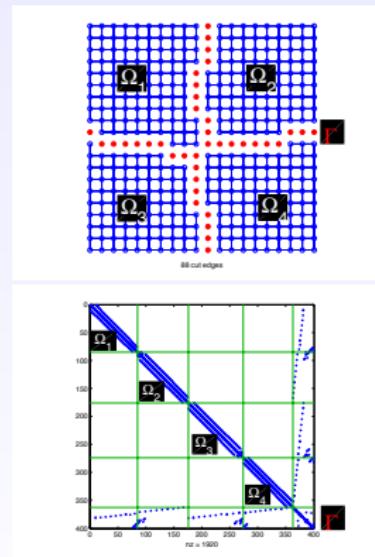
$$\mathcal{A}^{(i)} = \begin{pmatrix} \mathcal{A}_{\mathcal{I}_i \mathcal{I}_i} & \mathcal{A}_{\mathcal{I}_i \Gamma_i} \\ \mathcal{A}_{\Gamma_i \mathcal{I}_i} & \mathcal{A}_{\Gamma \Gamma}^{(i)} \end{pmatrix}$$

- ★ Local Schur Complement:

$$\mathcal{S}^{(i)} = \mathcal{A}_{\Gamma \Gamma}^{(i)} - \mathcal{A}_{\Gamma_i \mathcal{I}_i} \mathcal{A}_{\mathcal{I}_i \mathcal{I}_i}^{-1} \mathcal{A}_{\mathcal{I}_i \Gamma_i}$$

- ★ Algebraic Additive Schwarz Preconditioner

$$\mathcal{M} = \sum_{i=1}^N \mathcal{R}_{\Gamma_i}^T (\bar{\mathcal{S}}^{(i)})^{-1} \mathcal{R}_{\Gamma_i}$$



## Algebraic Additive Schwarz Preconditioner [ L.Carvalho, L.Giraud, G.Meurant 01]

$$\mathcal{M} = \sum_{i=1}^N \mathcal{R}_{\Gamma_i}^T (\bar{\mathcal{S}}^{(i)})^{-1} \mathcal{R}_{\Gamma_i}$$

$$\underbrace{\mathcal{S}^{(i)} = \begin{pmatrix} \mathcal{S}_{kk}^{(\iota)} & \mathcal{S}_{k\ell} \\ \mathcal{S}_{\ell k} & \mathcal{S}_{\ell\ell}^{(\iota)} \end{pmatrix}}_{\text{local Schur}} \implies \underbrace{\bar{\mathcal{S}}^{(i)} = \begin{pmatrix} \mathcal{S}_{kk} & \mathcal{S}_{k\ell} \\ \mathcal{S}_{\ell k} & \mathcal{S}_{\ell\ell} \end{pmatrix}}_{\text{local assembled Schur}}$$

$\sum_{\iota \in adj} \mathcal{S}_{\ell\ell}^{(\iota)}$

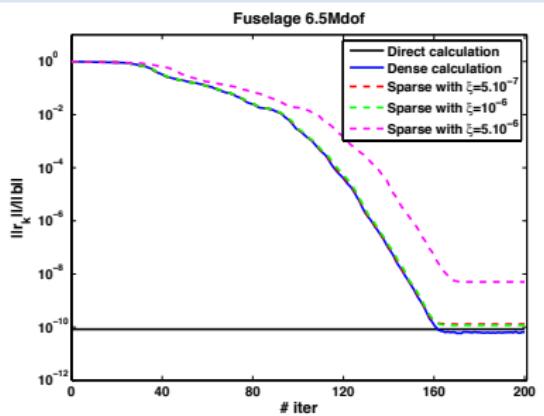
where  $\bar{\mathcal{S}}^{(i)}$  is obtained from  $\mathcal{S}^{(i)}$  via neighbor to neighbor comm

## Closely related work

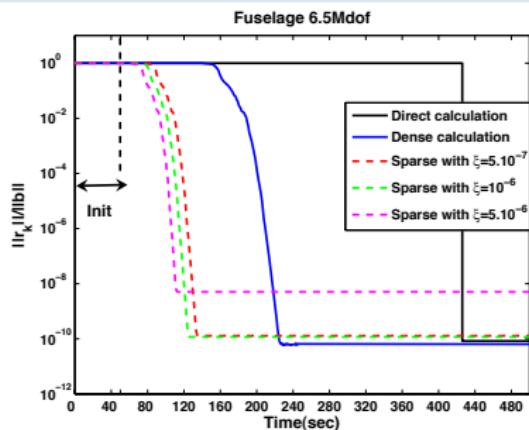
Similarity with Neumann-Neumann preconditioner [J.F Bourgat, R. Glowinski, P. Le Tallec and M. Vidrascu - 89] [Y.H. de Roek, P. Le Tallec and M. Vidrascu - 91]

# Numerical behaviour of sparse preconditioners

## Convergence history



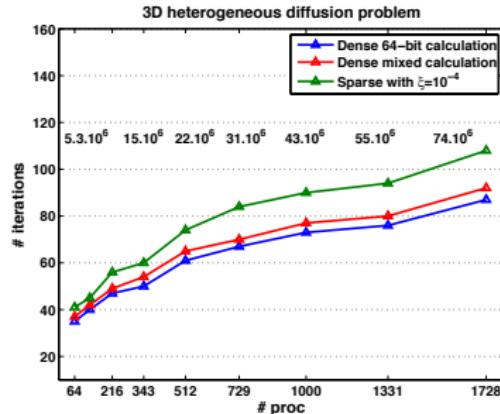
## Time history



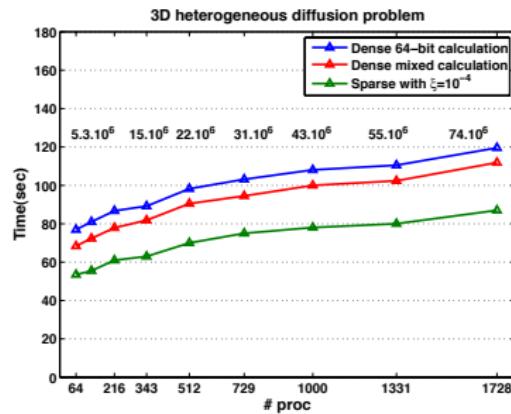
- ★ Fuselage problem of 6.5 M dof mapped on 16 processors
- ★ The sparse preconditioner setup is 4 times faster than the dense one (19.5 v.s. 89 seconds)
- ★ In term of global computing time, the sparse algorithm is about twice faster
- ★ The attainable accuracy of the hybrid solver is comparable to the one computed with the direct solver

# Scaled scalability on massively parallel platforms

## Numerical scalability



## Parallel performance



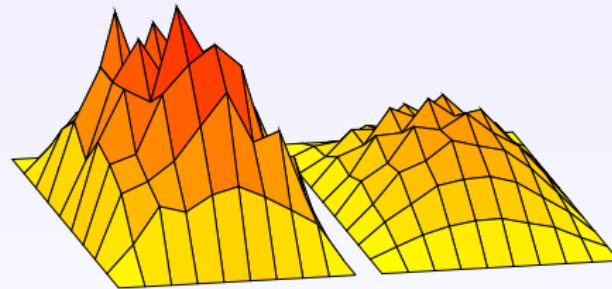
- ★ The solved problem size varies from 2.7 up to 74 M dof
- ★ Control the growth in the # of iterations by introducing a coarse space correction
- ★ The computing time increases slightly when increasing # sub-domains
- ★ Although the preconditioners do not scale perfectly, the parallel time scalability is acceptable
- ★ The trend is similar for all variants of the preconditioners using CG Krylov solver

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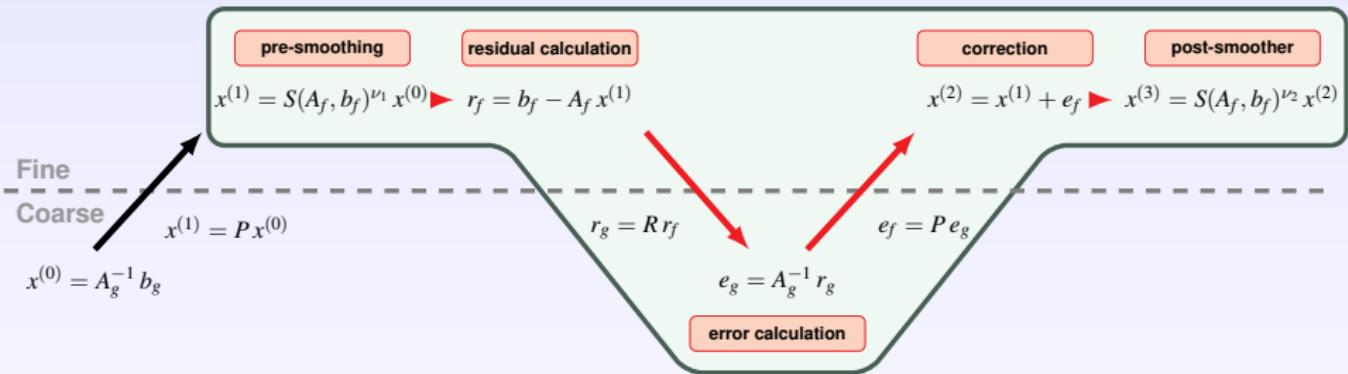
# Multigrid Underlying ideas

- ★ Stationary iterative schemes versus the error modes
  - ▶ The high frequency modes are damped quickly
  - ▶ The low frequency modes are damped very slowly



- ★ The low frequency modes might be viewed as high frequency on a coarser mesh

# Full-Multigrid

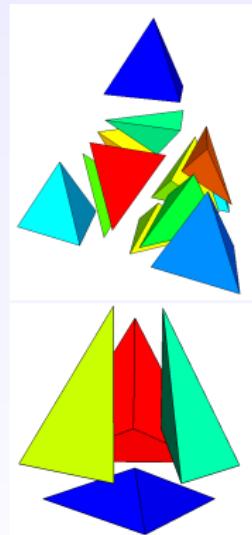


- ★ Factorization of coarse problem performed only once
- ★ Many forward/backward substitutions on coarsest grid
- ★ Grid transfer operators to move within hierarchical meshes
  - ▶ Fine → coarse : restriction
  - ▶ Coarse → fine : prolongation

# Refinement/Coarsening strategies

## Unstructured mesh refinement

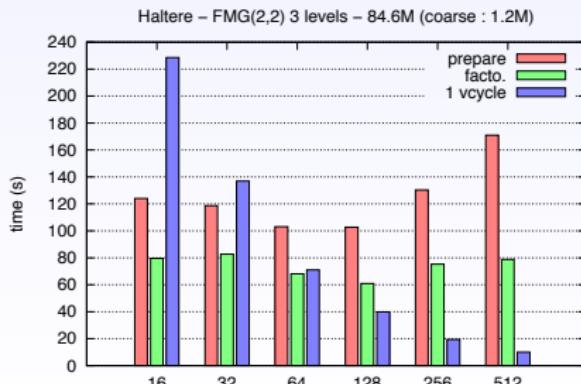
- ★ Isotropic refinement
  - + Preserve aspect ration
  - Large number of fine elements  
(x12)
  - Coupling interface change
  
- ★ Anisotropic refinement
  - + Coupling interface unchanged
  - + Slower increase of mesh size x4
  - Bad aspect ratio



# Strong scalability

Table: fine 84.6M – coarse 1.2 M – FMG(2,2) 3 levels

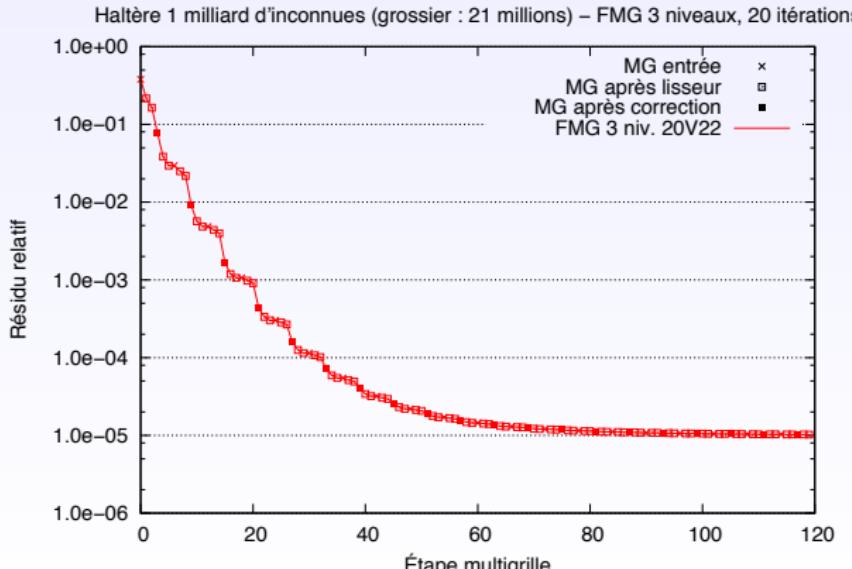
Cores	Init.	Assemb.	Facto.	Solve	10V
16	123.98	0.42	79.62	0.55	2285.58
32	118.67	0.23	82.72	0.30	1369.26
64	103.10	0.12	68.18	0.19	710.57
128	102.69	0.06	60.94	0.11	399.23
256	130.32	0.03	75.27	0.21	194.42
512	170.97	0.01	78.81	0.06	100.17



# Validation – Strong scaling

Table: fine 1.3B – coarse 21.1 M – FMG(2,2) 3 levels

Cores	Init.	Assemb.	Facto.	Solve	10V
1024	1160.28	0.14	147.73	0.55	857.69



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## What I haven't talked about, but we could !!

- ★ Dense linear algebra kernels on emerging platforms, numerical resilient algorithms, iterative solvers for multiples right-hand sides, eigensolvers
- ★ Code coupling
- ★ Material physics

## Sotware and collaborations

- ★ Available packages : HIPS, MaPHys, ScalFMM, EPSN
- ★ Ongoing collaborations: MORSE (KAUST, UCD, UTK), FAST-LA (LBNL, Stanford)

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Questions ?