

Solving Maxwell's equations with domain decomposition methods for brain imaging

Pierre-Henri Tournier

Laboratoire Jacques-Louis Lions

INRIA équipe ALPINES

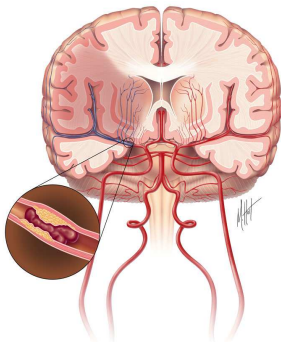
7th Tutorial and Workshop on FreeFem++

December 16, 2015

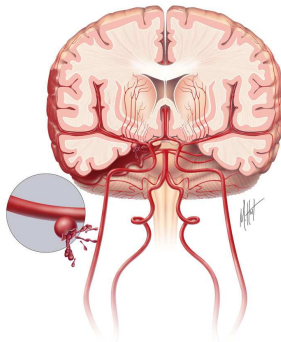
Motivation

2 types of stroke :

ischemic



hemorrhagic



The correct treatment depends on the type of stroke :

⇒ restore blood flow

⇒ lower blood pressure

Motivation

In order to differentiate between ischemic and hemorrhagic stroke, CT scan or MRI is typically used.

Microwave tomography is a novel and promising imaging technique, especially for medical and brain imaging.

	CT scan	MRI	microwave tomography
resolution	excellent	excellent	good
fast	-	-	✓
safe	-	✓	✓
mobile	-	-	✓
cost	~ 1 000 000 €	~1 000 000 €	~300 000 €

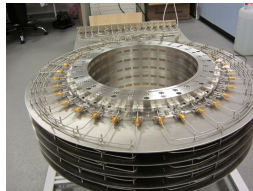
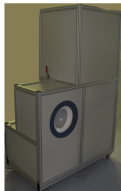
Diagnosing a stroke at the earliest possible stage is crucial for all following therapeutic decisions.

Motivation

EMTensor GmbH, Vienna, Austria.



First-generation prototype: cylindrical chamber composed of 5 rings of 32 antennas (ceramic-loaded waveguides).



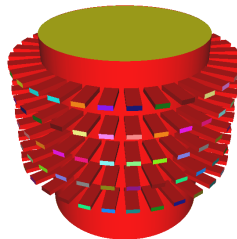
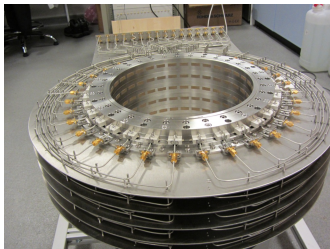
Motivation

MEDIMAX ANR project: development of a **new robust inversion tool associated with the electromagnetic forward problem** in highly heterogeneous media based on the high-level integrated development environment FreeFem++.

Partners:

- LEAT : Christian Pichot (project coordinator), Iannis Aliferis, Claire Migliaccio and Ibtissam El Kanfoud;
- JAD : Victorita Dolean, Francesca Rapetti, Richard Pasquetti and Marcella Bonazzoli;
- MAP5 : Maya de Buhan and Marion Darbas;
- LJLL : Frédéric Nataf, Frédéric Hecht, Antoine Le Hyaric and Pierre-Henri Tournier.

The direct problem

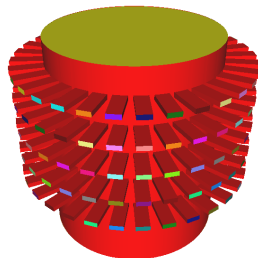


We consider in Ω a linear, isotropic, non-magnetic, dispersive, dissipative dielectric material.

The direct problem consists in finding the electromagnetic field distribution in the whole chamber, given a known material and transmitted signal.

The direct problem

For each of the 5×32 antennas, the associated electric field \mathbf{E}_i is the solution of Maxwell's equations:



$$(1) \quad \left\{ \begin{array}{ll} \nabla \times (\nabla \times \mathbf{E}_i) - \mu_0 (\omega^2 \varepsilon + i\omega \sigma) \mathbf{E}_i = \mathbf{0} & \text{in } \Omega, \\ \mathbf{E}_i \times \mathbf{n} = \mathbf{0} & \text{on } \Gamma_{\text{metal}}, \\ (\nabla \times \mathbf{E}_i) \times \mathbf{n} + i\beta \mathbf{E}_i \times \mathbf{n} = \mathbf{g} & \text{on } \Gamma_i, \\ (\nabla \times \mathbf{E}_i) \times \mathbf{n} + i\beta \mathbf{E}_i \times \mathbf{n} = \mathbf{0} & \text{on } \Gamma_j, j \neq i, \end{array} \right.$$

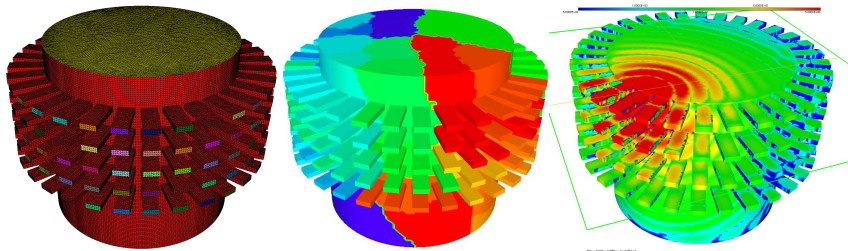
where μ_0 is the permittivity of free space, ω is the incident angular frequency, β is the wavenumber of the waveguide, $\varepsilon > 0$ is the dielectric permittivity and $\sigma > 0$ is the conductivity.

The direct problem

Spatial discretization using Nedelec finite elements yields a large sparse linear system $Au = f_i$ for each transmitting antenna i .

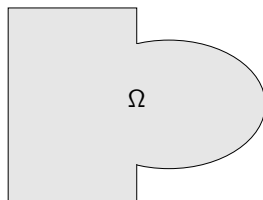
We need a robust and efficient solver for second order time-harmonic Maxwell's equations with heterogeneous coefficients.

⇒ Use domain decomposition methods to produce parallel preconditioners for the GMRES algorithm.



Overlapping domain decomposition methods

Consider the linear system: $Au = f \in \mathbb{R}^n$.



Overlapping domain decomposition methods

Consider the linear system: $Au = f \in \mathbb{R}^n$.

Given a decomposition of $\llbracket 1; n \rrbracket$, $(\mathcal{N}_1, \mathcal{N}_2)$, define:

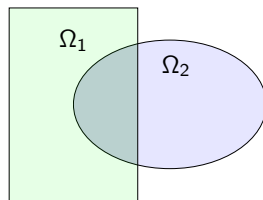
- ▶ the restriction operator R_i from $\llbracket 1; n \rrbracket$ into \mathcal{N}_i ,
- ▶ R_i^T as the extension by 0 from \mathcal{N}_i into $\llbracket 1; n \rrbracket$.

Then solve concurrently:

$$u_1^{m+1} = u_1^m + A_{11}^{-1} R_1(f - Au^m) \quad u_2^{m+1} = u_2^m + A_{22}^{-1} R_2(f - Au^m)$$

where $u_i = R_i u$ and $A_{ij} := R_i A R_j^T$.

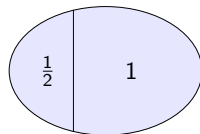
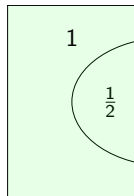
[Schwarz 1870]



Overlapping domain decomposition methods

Duplicated unknowns coupled via a *partition of unity*.

$$I = \sum_{i=1}^N R_i^T D_i R_i.$$



To solve $Au = f$ Schwarz methods can be viewed as preconditioners for a fixed point algorithm:

$$u^{n+1} = u^n + M^{-1}(f - Au^n).$$

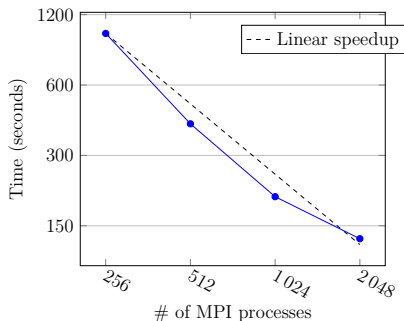
- ▶ $M_{\text{RAS}}^{-1} := \sum_{i=1}^N R_i^T D_i A_i^{-1} R_i$ with $A_i = R_i A R_i^T$
- ▶ $M_{\text{ORAS}}^{-1} := \sum_{i=1}^N R_i^T D_i B_i^{-1} R_i$ **Optimized transmission conditions**
[B. Després 1991] for Helmholtz

HPDDM

HPDDM is an efficient parallel implementation of domain decomposition methods

by Pierre Jolivet and Frédéric Nataf

- ▶ header-only library written in C++11 with MPI and OpenMP
- ▶ interfaced with FreeFem++



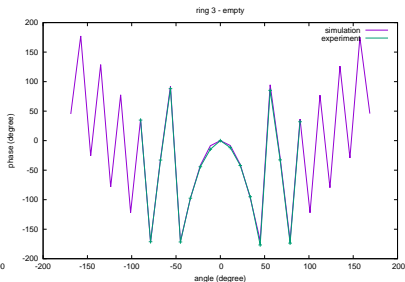
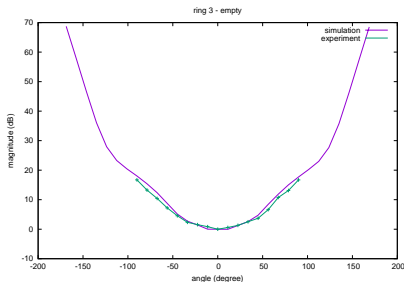
Strong scalability test for Maxwell 3D - 100M d.o.f.

Comparison with experiments

The experimental measurements obtained from the antennas are the reflexion and transmission coefficients

$$S_{ij}^{obs} = \frac{\int_{\Gamma_j} \overline{\mathbf{E}_i} \cdot \mathbf{E}_0 d\gamma}{\int_{\Gamma_j} |\mathbf{E}_0|^2 d\gamma}, \text{ for } i, j = 1, \dots, 160,$$

where \mathbf{E}_0 is the fundamental mode of the waveguide.



The inverse problem

For given ω , β and \mathbf{g} , the inverse problem consists in recovering ϵ and σ such that for each transmitting antenna i , the solution \mathbf{E}_i to the associated Maxwell's problem matches the observations:

$$\frac{\int_{\Gamma_j} \overline{\mathbf{E}_i} \cdot \mathbf{E}_0 d\gamma}{\int_{\Gamma_j} |\mathbf{E}_0|^2 d\gamma} = S_{ij}^{obs} \quad \text{for each receiving antenna } j.$$

Difficulties :

- ▶ inverse problems are ill-posed
- ▶ noise in the experimental data
- ▶ solving the inverse problem means solving the direct problem multiple times \implies time-consuming

The inverse problem

Solving the inverse problem corresponds to minimizing the following cost functional:

$$\begin{aligned} J(\kappa) &= \frac{1}{2} \sum_{i=1}^{160} \sum_{j=1}^{160} \left| S_{ij}(\kappa) - S_{ij}^{obs} \right|^2 \\ &= \frac{1}{2} \sum_{i=1}^{160} \sum_{j=1}^{160} \left| \frac{\int_{\Gamma_j} \overline{\mathbf{E}_i(\kappa)} \cdot \mathbf{E}_0 d\gamma}{\int_{\Gamma_j} |\mathbf{E}_0|^2 d\gamma} - S_{ij}^{obs} \right|^2, \end{aligned}$$

where $\kappa(x) \in \mathbb{C}$ and $S_{ij}(\kappa)$ depends on the solution $\mathbf{E}_i(\kappa)$ to

$$\left\{ \begin{array}{ll} \nabla \times (\nabla \times \mathbf{E}_i) - \kappa \mathbf{E}_i = \mathbf{0} & \text{in } \Omega, \\ \mathbf{E}_i \times \mathbf{n} = \mathbf{0} & \text{on } \Gamma_{\text{metal}}, \\ (\nabla \times \mathbf{E}_i) \times \mathbf{n} + i\beta \mathbf{E}_i \times \mathbf{n} = \mathbf{g} & \text{on } \Gamma_i, \\ (\nabla \times \mathbf{E}_i) \times \mathbf{n} + i\beta \mathbf{E}_i \times \mathbf{n} = \mathbf{0} & \text{on } \Gamma_j, j \neq i. \end{array} \right.$$

The inverse problem

$$J(\kappa) = \frac{1}{2} \sum_{i=1}^{160} \sum_{j=1}^{160} \left| S_{ij}(\kappa) - S_{ij}^{obs} \right|^2 = \frac{1}{2} \sum_{i=1}^{160} \sum_{j=1}^{160} \left| \frac{\int_{\Gamma_j} \overline{\mathbf{E}_i(\kappa)} \cdot \mathbf{E}_0 d\gamma}{\int_{\Gamma_j} |\mathbf{E}_0|^2 d\gamma} - S_{ij}^{obs} \right|^2$$

For $i = 1, \dots, 160$, we introduce the adjoint problem

$$\left\{ \begin{array}{ll} \nabla \times (\nabla \times \mathbf{F}_i) - \kappa \mathbf{F}_i = \mathbf{0} & \text{in } \Omega, \\ \mathbf{F}_i \times \mathbf{n} = \mathbf{0} & \text{on } \Gamma_{\text{metal}}, \\ (\nabla \times \mathbf{F}_i) \times \mathbf{n} + i\beta \mathbf{F}_i \times \mathbf{n} = \frac{S_{ij}(\kappa) - S_{ij}^{obs}}{\int_{\Gamma_j} |\mathbf{E}_0|^2 d\gamma} \bar{\mathbf{E}}_0 & \text{on } \Gamma_j. \end{array} \right.$$

We have

$$DJ(\kappa, \delta\kappa) = \sum_{i=1}^{160} \Re \left[\int_{\Omega} \delta\kappa \mathbf{E}_i \cdot \mathbf{F}_i dx \right].$$

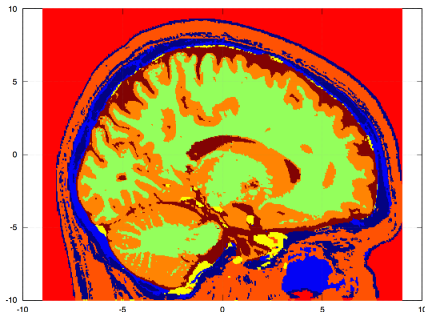
We can then compute the gradient to use in a gradient-based optimization algorithm.

some FreeFem++ code

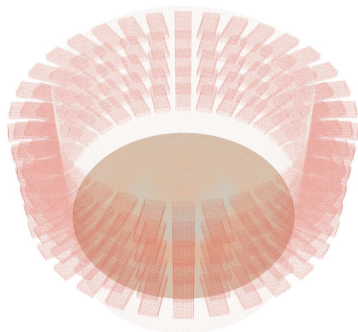
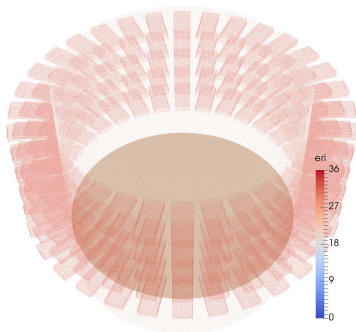
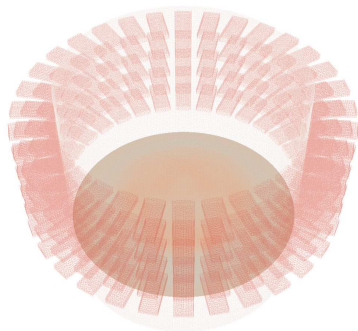
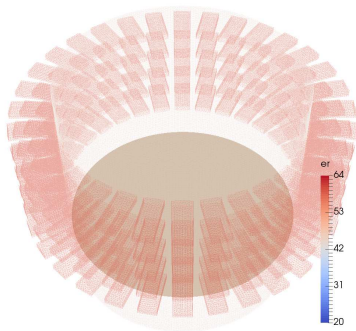
```
fespace Wh(Th, Edge03d); // local FE space
fespace WhP1(Th, P1);
macro generateTh(nm) nm = readmesh3("global.mesh"); // EOM
build(generateTh, Th, ThBorder, ThOverlap, s, D,
      numberIntersection, arrayIntersection,
      restrictionIntersection, Wh, Pk, commrhs, 0)
...
macro Varf(varfName, meshName, PhName)
  varf varfName([Ex, Ey, Ez], [vx, vy, vz]) =
    int3d(meshName, qforder=qforder)(Curl(vx, vy, vz)'*Curl(Ex,
      Ey, Ez))
    -int3d(meshName, qforder=qforder)((2*pi*f/c0)^2*(er+
      kappariaug+1.i*kappaiaug)*[vx, vy, vz]'*[Ex, Ey, Ez])
    -int2d(meshName, qforder=qforder, tlabwps)(1.i*betawg*
      CrossN(vx, vy, vz)'*CrossN(Ex, Ey, Ez))
    CLtopbottom(meshName, er+kappariaug+1.i*kappaiaug)
    + on(labmetal, Ex=0, Ey=0, Ez=0); // EOM
...
assemble(mat, rhs, Wh, Th, ThBorder, Varf, VarfOpt)
zschwarz A(mat, arrayIntersection, restrictionIntersection,
  scaling = D, communicator = commrhs);
...
DDM(A, nEx, Bi, O=Opt, excluded=0, timing=stats);
```

Numerical experiment - hemorrhagic stroke

- ▶ Brain model from X-ray data ($362 \times 434 \times 362$)



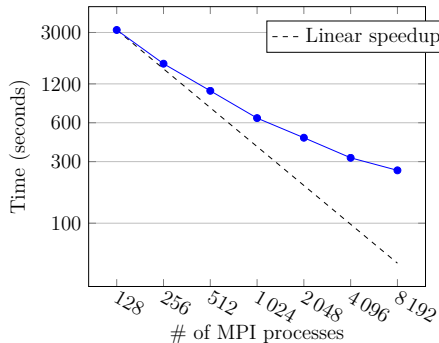
- ▶ $f = 1GHz$
- ▶ waveguides (ceramic) : $\epsilon_r = 59$
- ▶ matching liquid : $\epsilon_r = 44 + 20i$
- ▶ 10% white Gaussian noise on synthetic data
- ▶ reconstruction obtained after 45 minutes using 4096 processors of the Curie supercomputer (CEA).



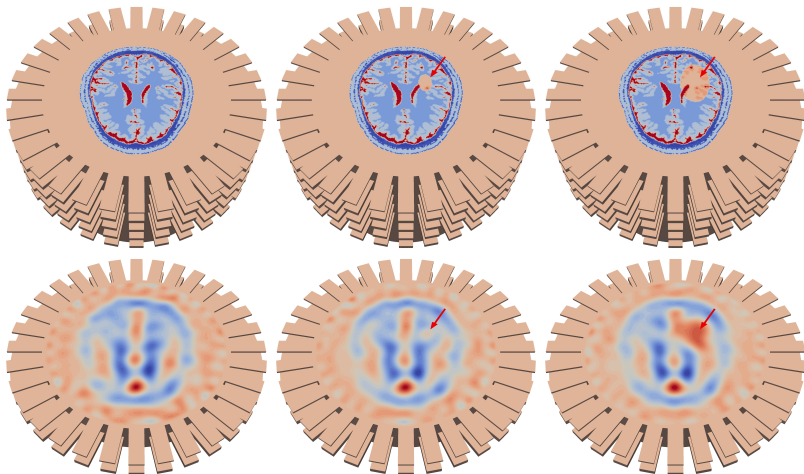
Numerical experiment - hemorrhagic stroke

Idea: reconstruct the permittivity slice by slice, by taking into account the transmitting antennas corresponding to only one ring and truncating the computational domain.

⇒ Reconstructed images corresponding to one ring obtained in less than 5 minutes.



Numerical experiment - hemorrhagic stroke



Current work and perspectives

- ▶ experimental data from EMTensor
- ▶ use recycling techniques for multiple right hand sides and between iterations during the optimisation process
- ▶ choose a good coarse space for a two-level scalable preconditioner for Maxwell's equations
- ▶ high-order edge elements