Acoustic Full-Waveform Inversion in Julia on Multi-xPUs

Giacomo Aloisi, Andrea Zunino, Christian Boehm, Andreas Fichtner

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Outline

1. Introduction to Full-Waveform Inversion
2. Theory and implementation
3. Numerical experiments and benchmarks
4. Conclusions and future work

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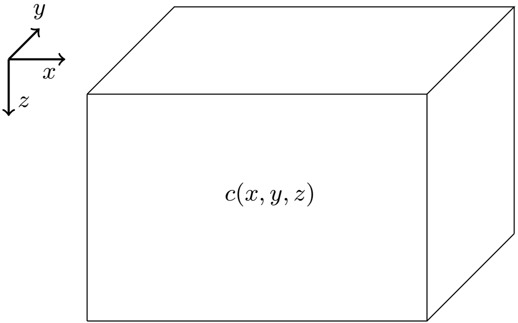
An introduction to (acoustic) Full-Waveform Inversion (FWI)



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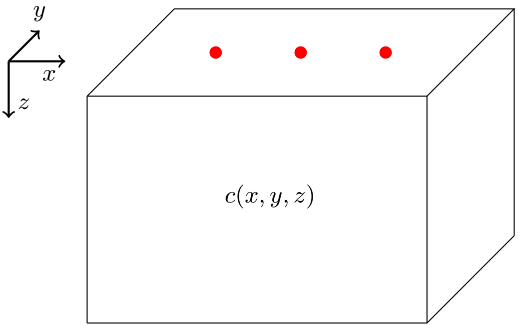

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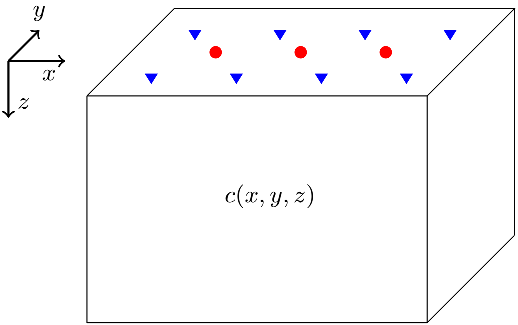

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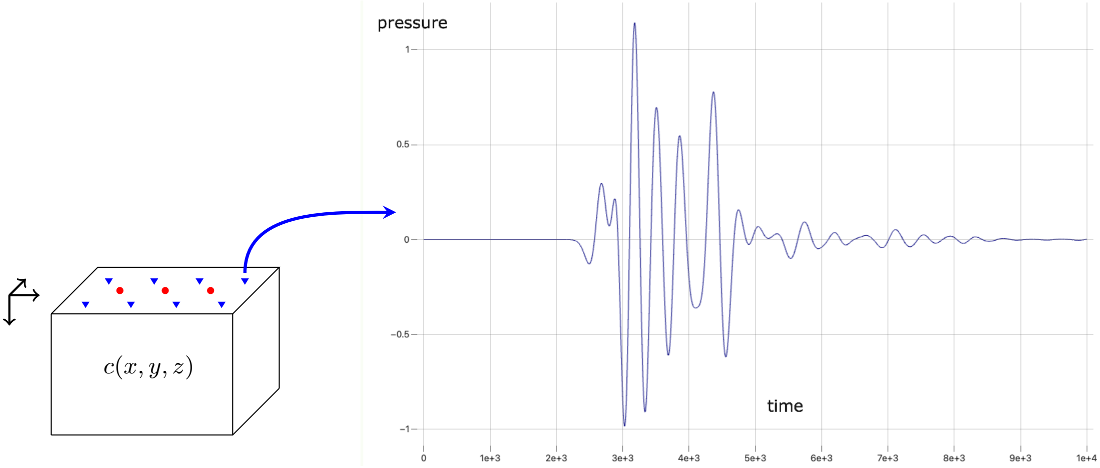

FWI applications: seismic tomography

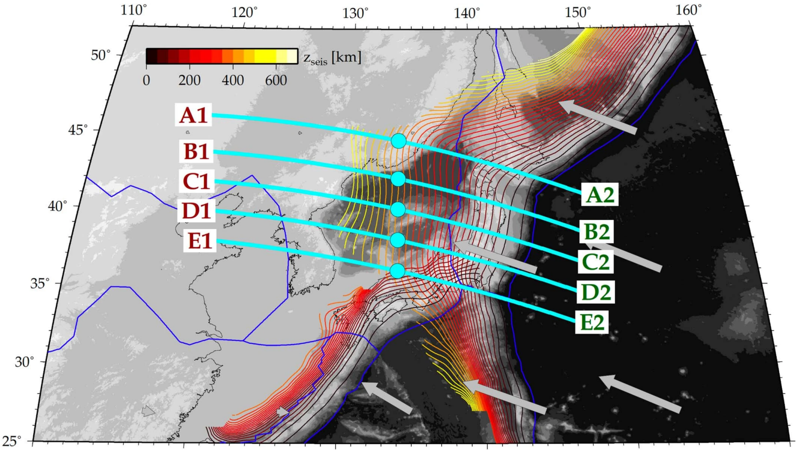

Figure from Gerya et al., 2021: Dynamic slab segmentation due to brittle–ductile damage in the outer rise
Data from Hayes et al., 2018: Slab2, a comprehensive subduction zone geometry model

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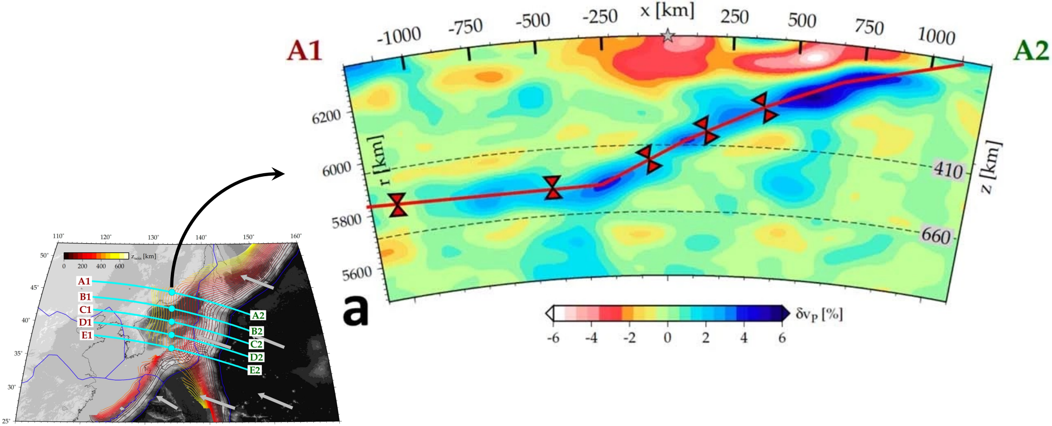

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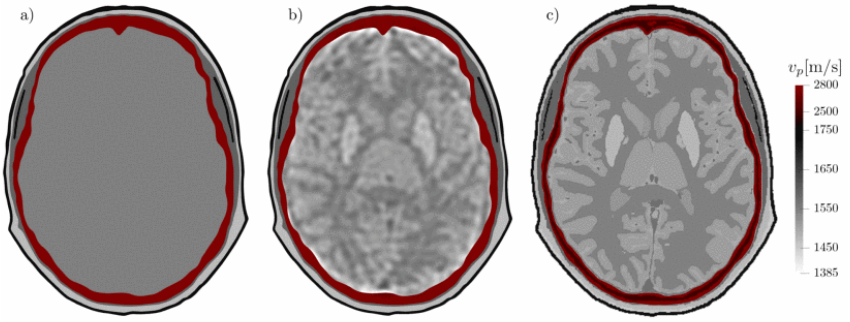
Data from Tao et al., 2018: Seismic Structure of the Upper Mantle Beneath Eastern Asia From Full Waveform Seismic Tomography

FWI applications: medical ultrasound tomography



initial model   reconstruction   target model

Figure from Marty et al., 2022: Elastic Full-Waveform Inversion for Transcranial Ultrasound Computed Tomography using Optimal Transport

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Solving the forward problem: acoustic wave equation

Acoustic wave PDE with homogeneous Dirichlet BDCs

$\Omega \subset \mathbb{R}^n, t \in [0,T], p = p(\boldsymbol{x},t) : \mathbb{R}^n \times [0,T] \to \mathbb{R}, s = s(\boldsymbol{x},t) : \mathbb{R}^n \times [0,T] \to \mathbb{R}, c = c(\boldsymbol{x}) : \mathbb{R}^n \to \mathbb{R}$

$$\begin{aligned} \frac{1}{c(\boldsymbol{x})^2}\frac{\partial^2 p(\boldsymbol{x},t)}{\partial t^2} &= \nabla_x^2\, p(\boldsymbol{x},t) + s(\boldsymbol{x},t) && , \text{ in } \overline{\Omega} \times [0,T], \\ p(\boldsymbol{x},t) &= 0 && , \text{ in } \partial\Omega \times [0,T] \end{aligned}$$

Solving the forward problem: acoustic wave equation

Acoustic wave PDE with C-PML BDCs

Let $\tilde{\partial}_i\Omega$ be and extension of $\partial\Omega$ in the direction i.

$$
\begin{aligned}
\frac{1}{c^2}\frac{\partial^2 p}{\partial t^2} &= \nabla_x^2\, p + s && \text{, in } \overline{\Omega} \times [0, T], \\
\frac{1}{c^2}\frac{\partial^2 p}{\partial t^2} &= \nabla_x^2\, p + \frac{\partial \psi_i}{\partial i} + \xi_i && \text{, in } \tilde{\partial}_i\Omega \times [0, T]
\end{aligned}
$$

Solving the forward problem: acoustic wave equation

2D acoustic wave discretization with central FD (2nd order in space and time)

$$
\begin{aligned}
p_{x,y}^{t+1} &= 2p_{x,y}^{t} - p_{x,y}^{t-1} \\
&\quad + c_{x,y}^2 \Delta t^2 \left(\frac{p_{x+1,y}^{t} - 2p_{x,y}^{t} + p_{x-1,y}^{t}}{\Delta x^2} \right) \\
&\quad + c_{x,y}^2 \Delta t^2 \left(\frac{p_{x,y+1}^{t} - 2p_{x,y}^{t} + p_{x,y-1}^{t}}{\Delta y^2} \right) \\
&\quad + c_{x,y}^2 \Delta t^2 s_{x,y}^{t} \qquad\qquad , \forall t \in [0, T], (x, y) \in \overline{\Omega}
\end{aligned}
$$

Misfit functional and minimization problem

$$\chi = \chi[p(c)] = \frac{1}{2}\sum_r (\boldsymbol{p}_r - \boldsymbol{p}_r^{\mathsf{obs}})\ \boldsymbol{C}_r^{-1}\ (\boldsymbol{p}_r - \boldsymbol{p}_r^{\mathsf{obs}})$$

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Time to compute χ on a 2000x2000 grid for 1000 time steps on 1 GPU $\approx$ 0.4 seconds

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Time to compute χ on a 2000x2000 grid for 1000 time steps on 1 GPU $\approx$ 0.4 seconds
Time to compute gradient $\rightarrow$ $16 * 10^5$ seconds $\approx$ 444 hours! NOT feasible!

Efficiently computing model parameters gradients: adjoint equation

$$G(p, c) := \nabla_x^2 \, p + s - \frac{1}{c^2}\frac{\partial^2 p}{\partial t^2} = 0$$

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$$\mathcal{L}$$

$$\frac{\partial \mathcal{L}}{\partial c_i} \overset{G \overset{!}{=} 0}{\overset{\downarrow}{=}} \frac{\partial \chi}{\partial c_i} = \frac{2}{c_i^3}\int_0^T \lambda \frac{\partial^2 p}{\partial t^2} dt$$

$$\frac{\partial \mathcal{L}}{\partial p} \qquad \times [T, 0]$$

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Efficiently computing model parameters gradients: adjoint equation

Time to gradient $\approx$ 1.8 seconds!

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4. Solve adjoint equation to get adjoint field λ
5. Compute $\nabla_c \chi$ while solving adjoint equation
6. Update model c using $\chi(p)$ and $\nabla_c \chi$ with an optimization algorithm (GD, L-BFGS, etc...) and go back to step 2. until convergence

HMCLab.jl and SeismicWaves.jl

HMCLab

https://hmclab.science, https://ptsolvers.github.io/GPU4GEO

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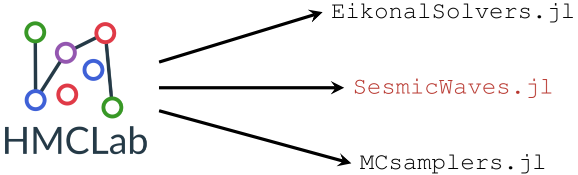

and more...

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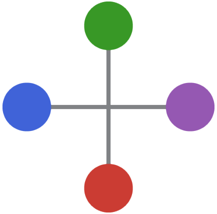
Code: single xPU 2D kernel w/ `ParallelStencil.jl`

```julia
@parallel_indices (i, j) function update_p(
    pold, pcur, pnew, halo, c, dt, dx, dy
)
    # pressure derivatives in space
    d2p_dx2 = (pcur[i+1, j] - 2.0 * pcur[i, j] + pcur[i-1, j]) / (dx^2)
    d2p_dy2 = (pcur[i, j+1] - 2.0 * pcur[i, j] + pcur[i, j-1]) / (dy^2)
    # update pressure
    pnew[i, j] = 2.0 * pcur[i, j] - pold[i, j] + c[i, j]^2 * dt^2 * (d2p_dx2 + d2p_dy2)

    return nothing
end
```

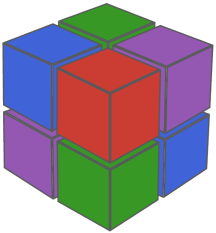


```julia
...
for it = 1:nt
    # update pressure
    @parallel (2:(nx-1), 2:(ny-1)) update_p(pold, pcur, pnew, halo, c, dt, dx, dy)
    # inject sources
    @parallel (1:nsrcs) inject_sources(pnew, dt2srctf, possrcs, it)
    # record receivers
    @parallel (1:nrecs) record_receivers(pnew, traces, posrecs, it)
    # swap pointers
    pold, pcur, pnew = pcur, pnew, pold
end
...
```

Omlin S. (CSCS), Räss L. (ETH) [https://github.com/omlins/ParallelStencil.jl]

Code: multi-xPU 2D kernel
w/ `ParallelStencil.jl` + `ImplicitGlobalGrid.jl`

```
...
for it = 1:nt
    @hide_communication b_width begin
        # update pressure
        @parallel (2:(nx-1), 2:(ny-1)) update_p(pold, pcur, pnew, halo, c, dt, dx, dy)
        # inject sources
        @parallel (1:nsrcs) inject_sources(pnew, dt2srctf, possrcs, it)
        # record receivers
        @parallel (1:nrecs) record_receivers(pnew, traces, posrecs, it)
        # exchange new pressure with other nodes
        update_halo(pnew)
    end
    # swap pointers
    pold, pcur, pnew = pcur, pnew, pold
end
...
```



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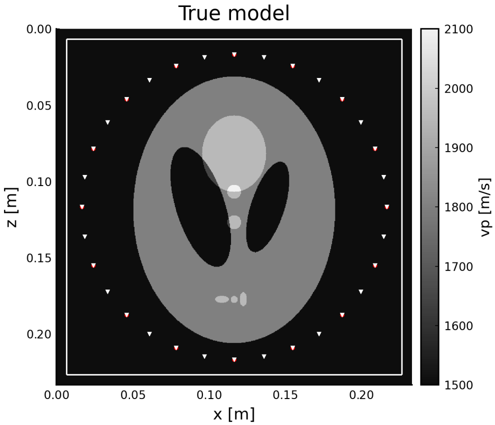
Numerical experiments: Shepp-Logan phantom inversion

Inversion setup
Sources: 16
Receivers: 32
Ricker wavelet at various frequencies
Model size: 701x701
C-PML layers: 20
Timesteps forward: 12000
Optim algo: L-BFGS



Shepp L., Logan B., 1974: The Fourier Reconstruction of a Head Section

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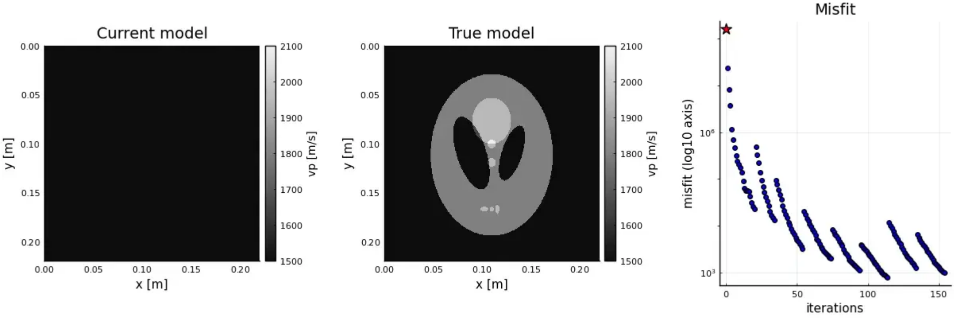

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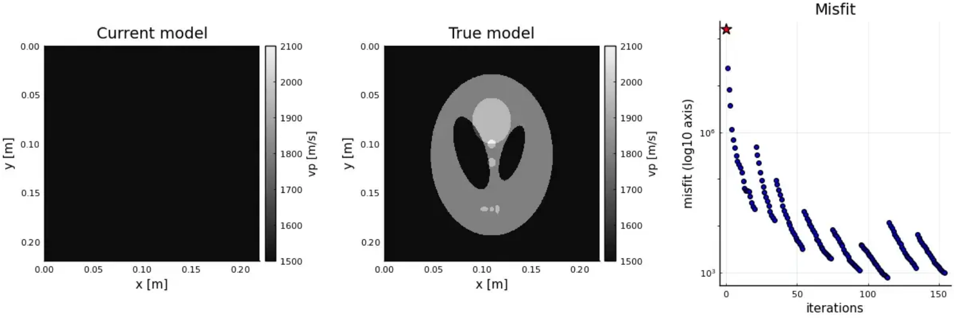

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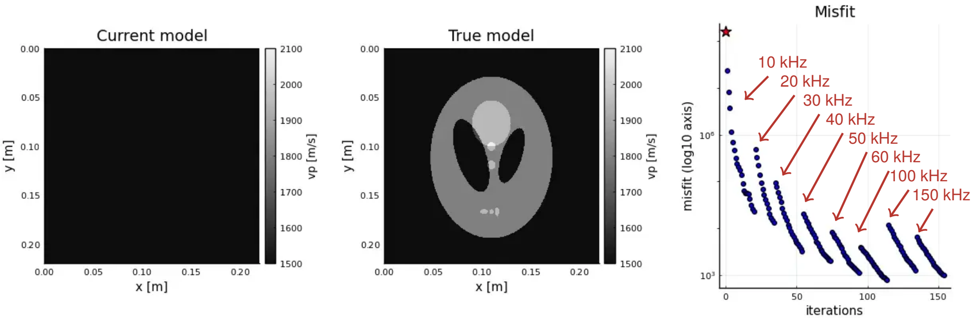
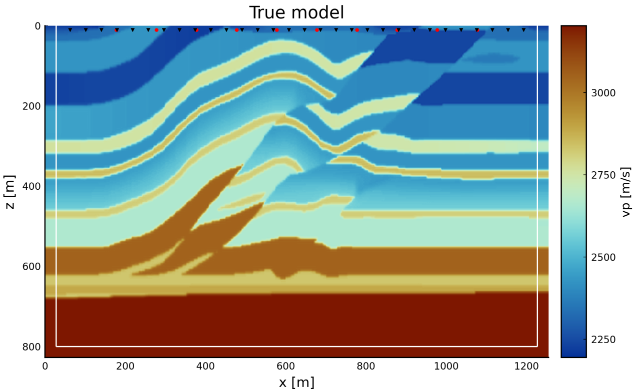


Numerical experiments: Overthrust model inversion (with correlated source noise)

Inversion setup
Sources: 10
Receivers: 30
Ricker wavelet at 12Hz
Model size: 896x594
C-PML layers: 20
Free surface BDC at top
Timesteps forward: 2500
Optim algo: L-BFGS



SEG/EAGE Salt and Overthrust Models [https://wiki.seg.org/wiki/SEG/EAGE_Salt_and_Overthrust_Models]

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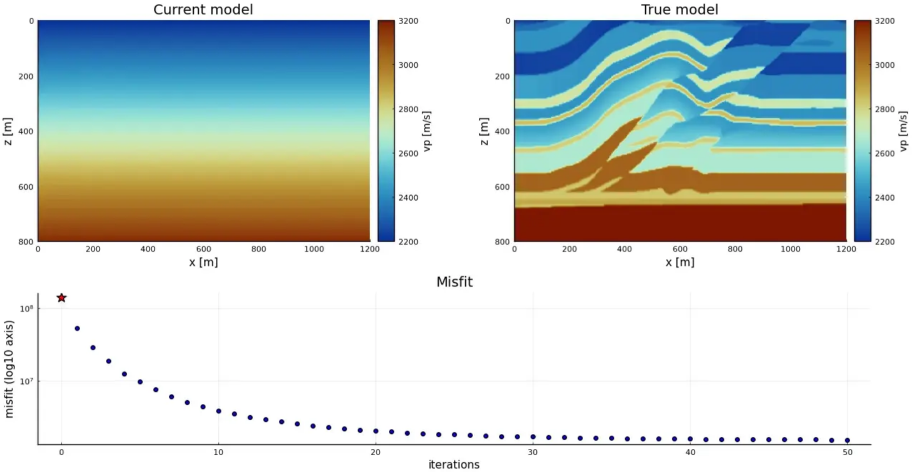

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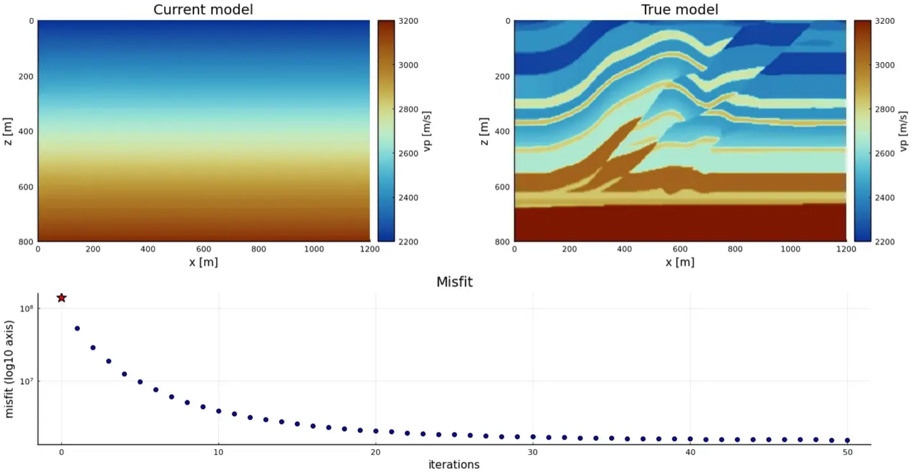

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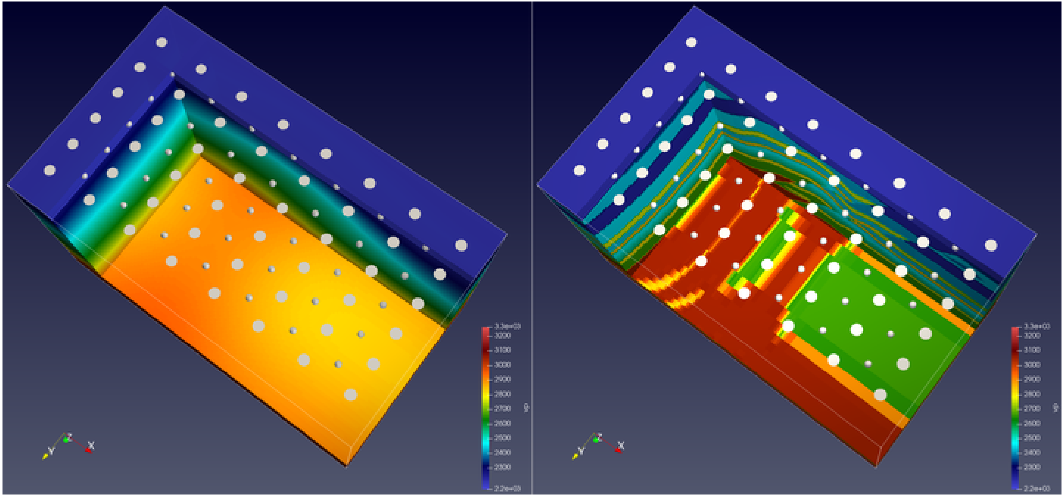

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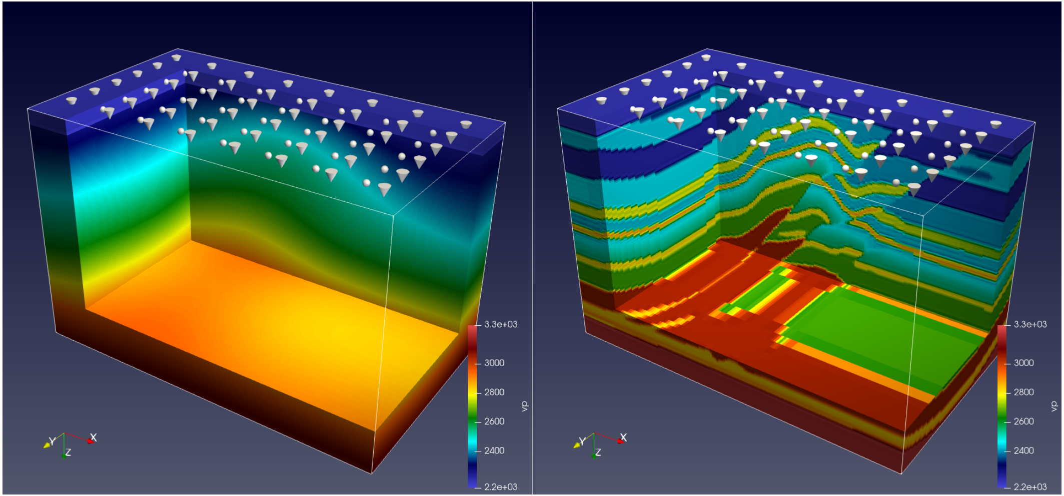

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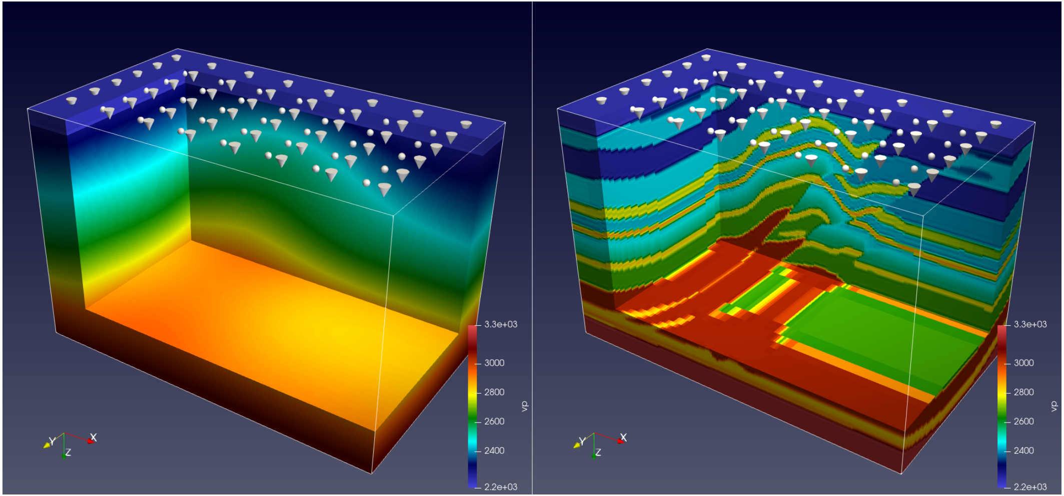

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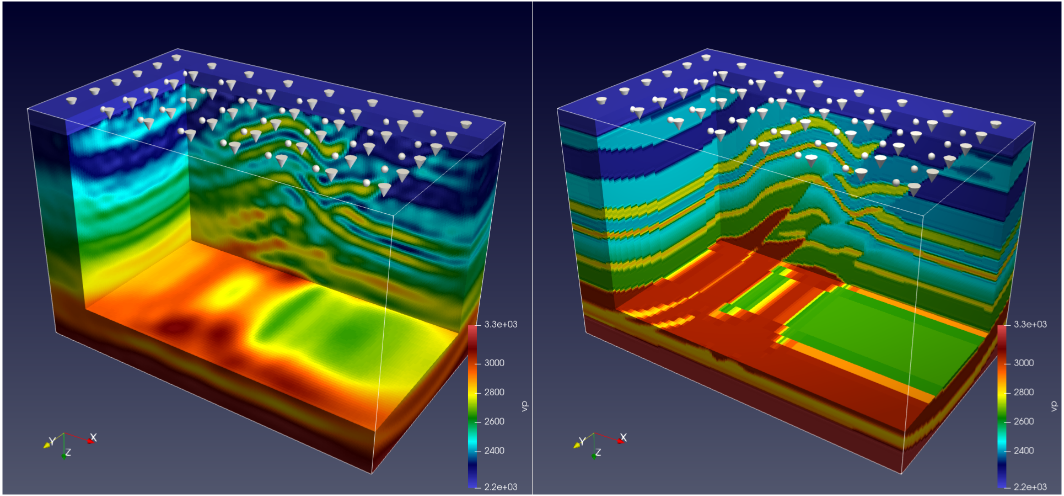

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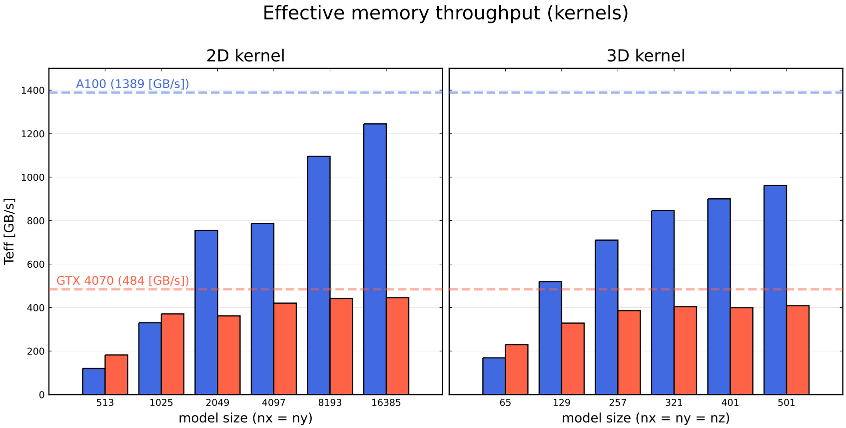
Benchmarks: kernels performance

Benchmarking setup
GPUs Nvidia GTX 4070 & A100
julia version 1.8.5
flags: -O3 –check-bounds=no
CUDA version:
12.1 (for GTX 4070)
11.4 (for A100)
Peak performances measured with GPU-STREAM
20 C-PML layers in each boundary



Repeated measurements until +-5% of median execution time is within the 99% non-parametric CI

Benchmarks: kernels performance

Benchmarking setup
GPUs Nvidia GTX 4070 & A100
julia version 1.8.5
flags: -O3 –check-bounds=no
CUDA version:
12.1 (for GTX 4070)
11.4 (for A100)
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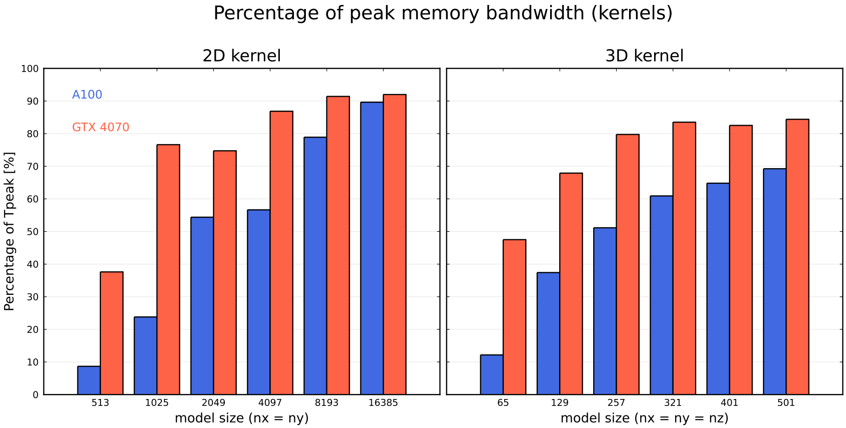

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Benchmarks: forward solver execution times

Benchmarking setup
GPU Nvidia GTX 4070
julia version 1.8.5
flags: -O3 –check-bounds=no
CUDA version: 12.1
Peak performances measured with GPU-STREAM
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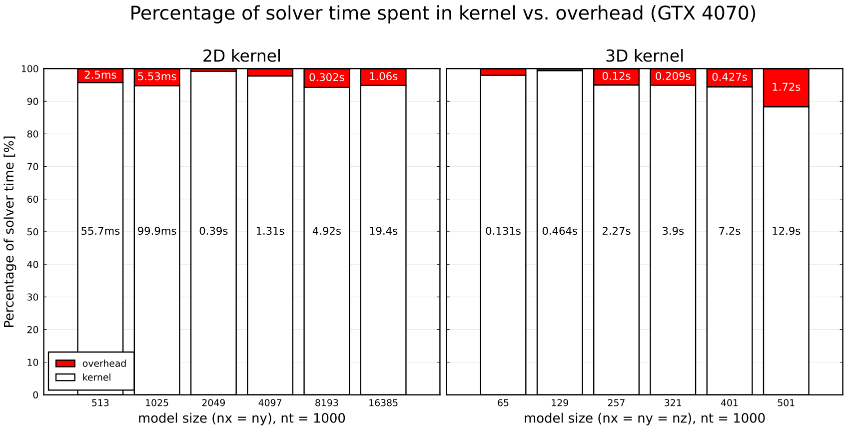
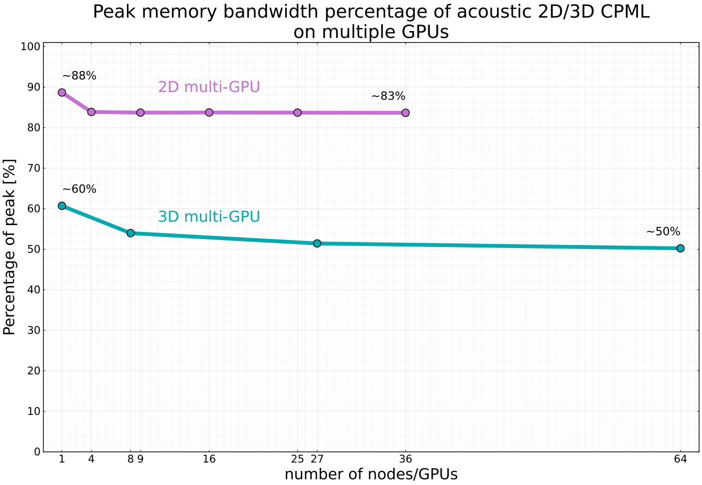


Benchmarks: (preliminary) multi-GPU weak scaling

Benchmarking setup
GPUs Tesla P100 (on Piz Daint)
julia version 1.7.1
flags: -O3 –check-bounds=no
Peak performances measured with GPU-STREAM
20 C-PML layers in each boundary



Measured average time per iteration by running multiple iterations (skip first 200 iterations for 2D, skip first 19 iterations for 3D)

Outline

1. Introduction to Full-Waveform Inversion
2. Theory and implementation
3. Numerical experiments and benchmarks
4. Conclusions and future work

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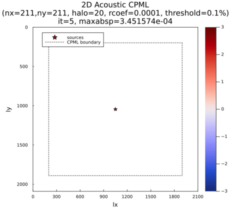
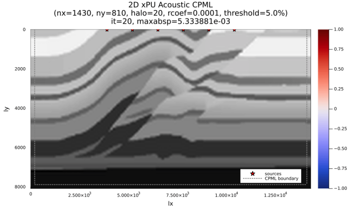
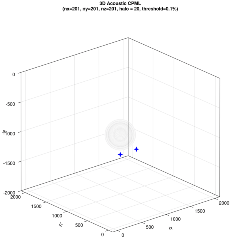
  - Fully fledged multi-xPU implementations

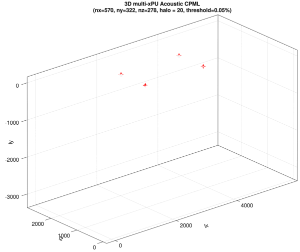
Thanks for your attention!

Giacomo Aloisi
[galoisi@student.ethz.ch]

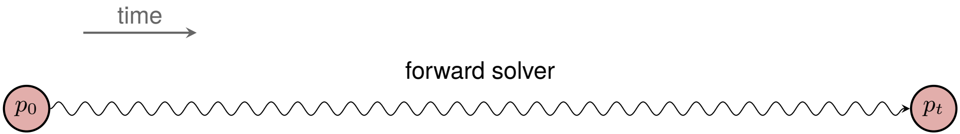








Efficiently computing model parameters gradients: checkpointing



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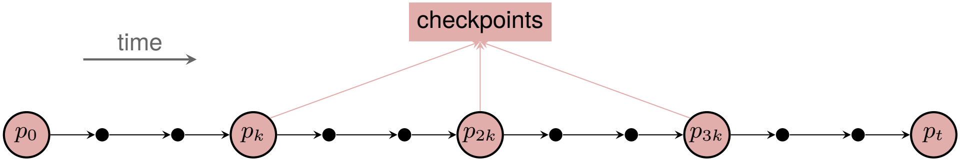

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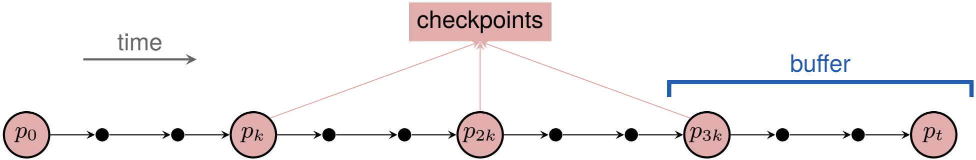

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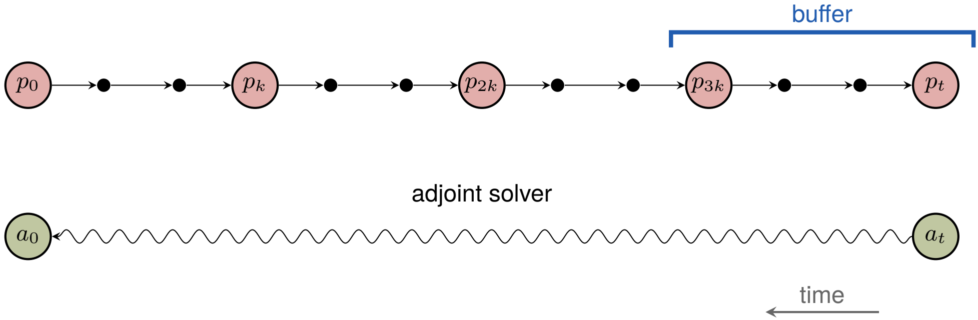

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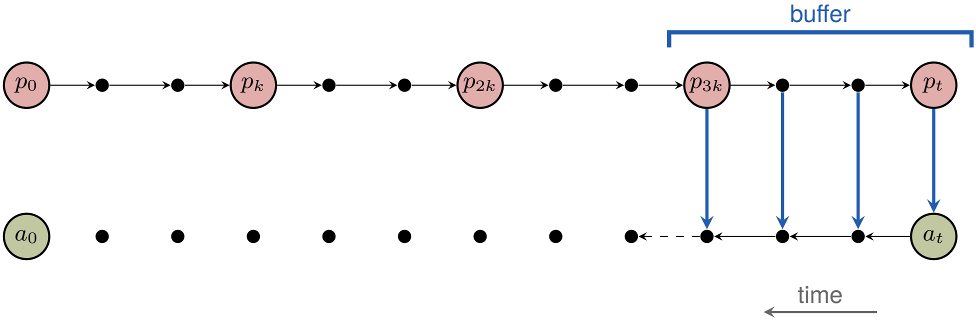

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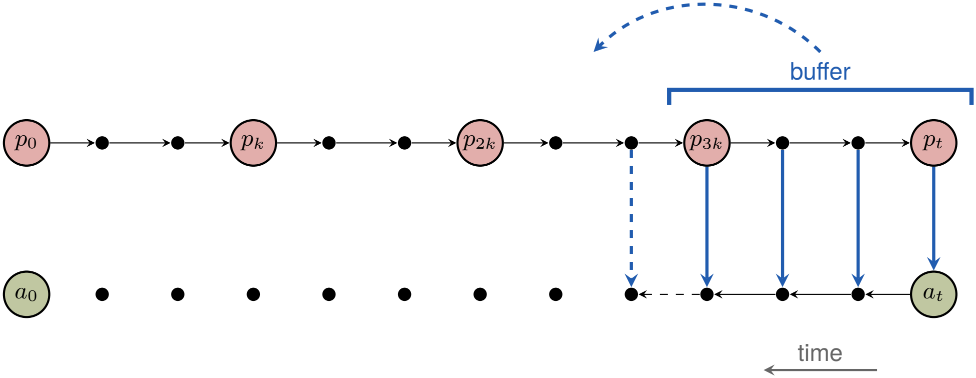

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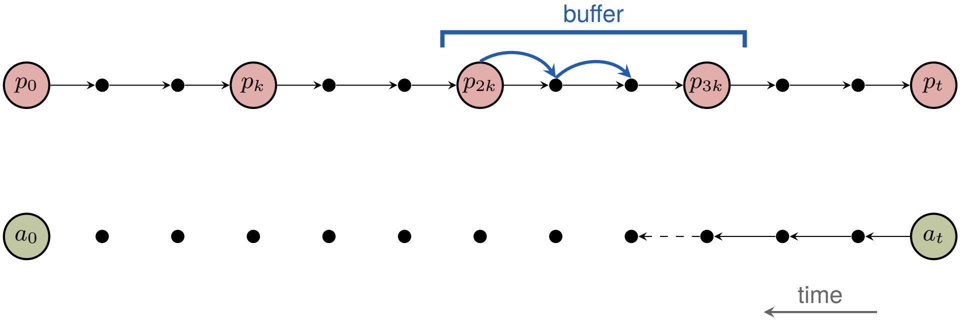

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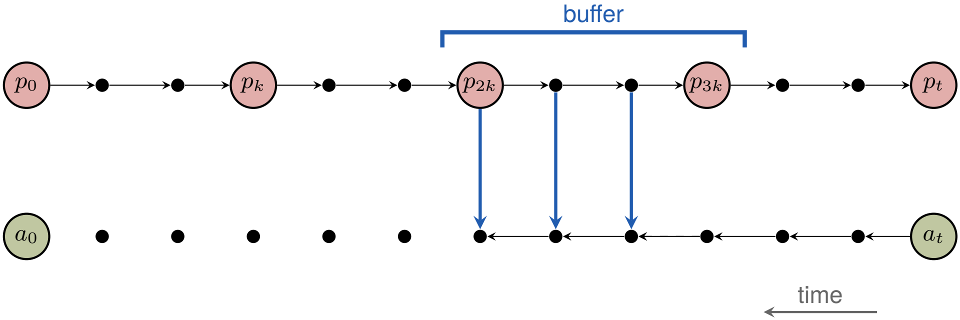

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