Numerical investigation of a multi-step one-shot method for frequency domain acoustic full waveform inversion

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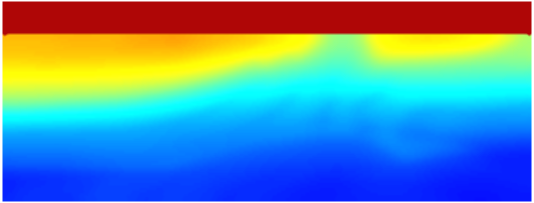
Introduction

Full waveform inversion (FWI) (I)

FWI is an **imaging method** that reconstructs physical properties of a sample by **minimizing** the mismatch between measured wave scattering data on the boundary of the sample and data obtained by **full-wave simulations**



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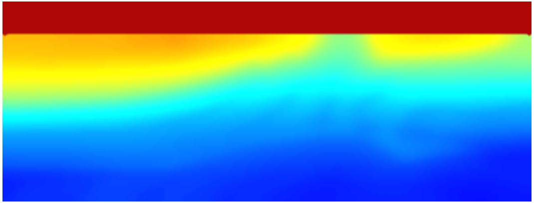

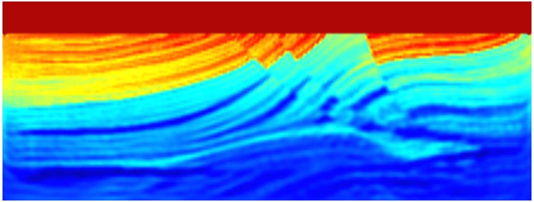

Full waveform inversion (FWI) (II)

In the **frequency domain**, FWI of the **squared wave slowness** field m amounts to the inversion of the forward Helmholtz problem

$$\begin{cases} \Delta_x u + \omega^2 m u & = b \\ \partial_n u + \imath\omega\sqrt{m} u & = 0 \end{cases} \implies A(m)u = b$$

by minimizing an error functional J between observed data at receivers d and the waveform u induced by the squared wave slowness m

$$\arg\min_m J(u(m)) \text{ with } u(m) = u \text{ such that } A(m)u = b$$

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Minimization with first- and second-order methods requires the gradient of $J(u(m))$, obtained by solving the **forward** and **adjoint** problems.

We focus on the one-shot paradigm applied to solve of the **linearized inverse problem**. Linearizing around the background slowness $\tilde{m}$ and waveform field $\tilde{u}$ such that

$$m = \tilde{m} + \delta m \text{ and } u = \tilde{u} + \delta u$$

Solving the linearized inverse problem therefore becomes finding δm such that

$$\arg\min_{\delta m} \tilde{J}(\delta u(\delta m)) \text{ with } \delta u(\delta m) = \delta u \text{ with } A(\tilde{m})\delta u = -\omega^2 \tilde{U} \delta m$$

Linearized inverse problem

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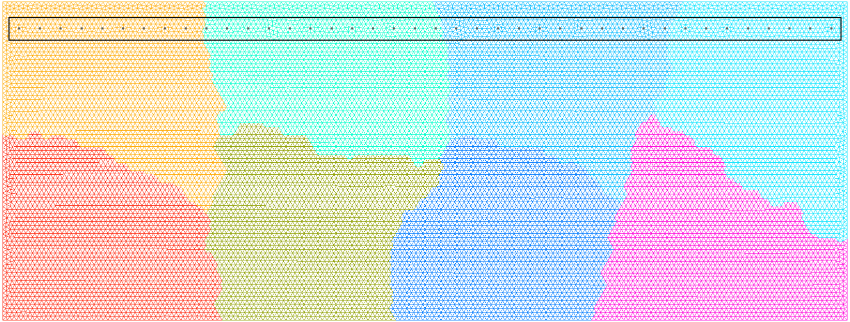
The linearized problem has a **constant system matrix** and its misfit functional is **convex**

Domain decomposition method

Computing the gradient requires solving the **forward** and **adjoint** problems. We focus on iteratively solving these linear systems using an **ORAS** preconditioner for the partitioned domain



Reference iterative FWI

When the forward and adjoint problems are solved iteratively, the inversion algorithm has the form

Reference iterative FWI

$\delta u^0 = 0; \lambda^0 = 0$
for $n = 1, 2, \dots$ **do**
  $\delta u_0^n = \delta u^{n-1}$; $\lambda_0^n = \lambda^{n-1}$
  for $\ell = 1, 2, \dots, a$ **do**
    $\delta u_\ell^n = \langle \ell\text{-th iterate of } \texttt{solve} \text{ for } \tilde{A}\delta u = -\omega^2 \tilde{U} \delta m^n \rangle$
  end for
  for $\ell = 1, 2, \dots, b$ **do**
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  $\delta u^n = \delta u_a^n$; $\lambda^n = \lambda_b^n$
  $g^n = \texttt{grad}(\delta u^n, \lambda^n)$
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    end for
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One-step one-shot

The one-shot paradigm consists in iterating on the forward & adjoint solvers concurrently to the minimization

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6: $\quad \delta m^{n+1} = \langle n$-th iterate of `optimize`$\rangle$
7: **end for**

When the system solver is the **stationary iteration** and the minimization scheme is **fixed-step gradient descent**, this converges under some conditions (Bonazzoli, Haddar and Vu, 2022)

Multi-step one-shot

Multi-step one-shot increases the amount of forward & adjoint solver iterations done per minimization step and limits them to k

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end for

Fixed-step gradient descent

Stationary iteration: convergence map (I)

The convergence behavior of the multi-step one-shot algorithm is mapped as a function of k and the step size τ for the Marmousi reference model at $1\,\mathrm{Hz}$

- 100 multi-step one-shot **gradient descent iterations** with a **stationary forward & adjoint solver** are run with a given k and τ

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- This cost is compared with the **reference iterative FWI** with a relative residual criterion of 10^{-6} for solves

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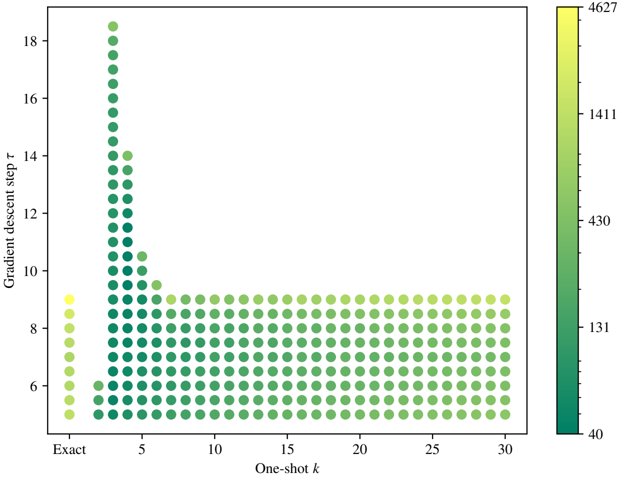

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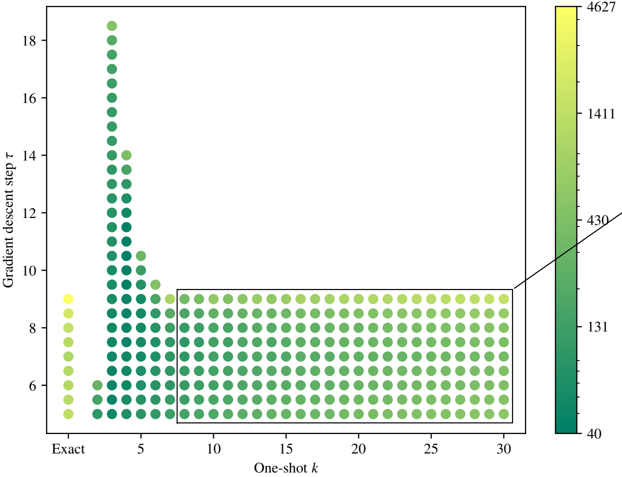

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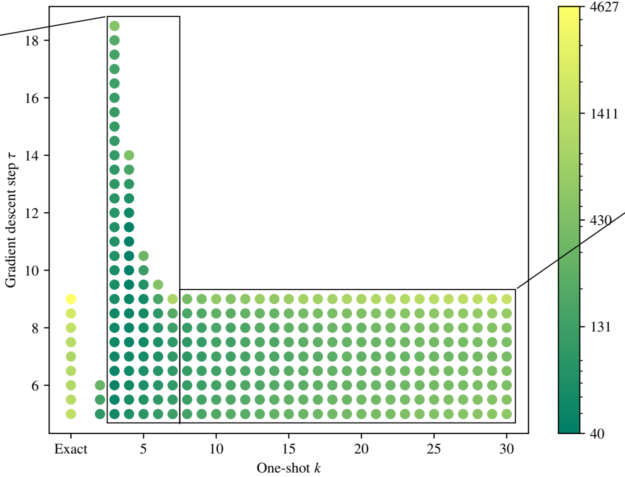
Maximal allowable step size $\tau_{\max}$ has a significant peak above the reference gradient regime



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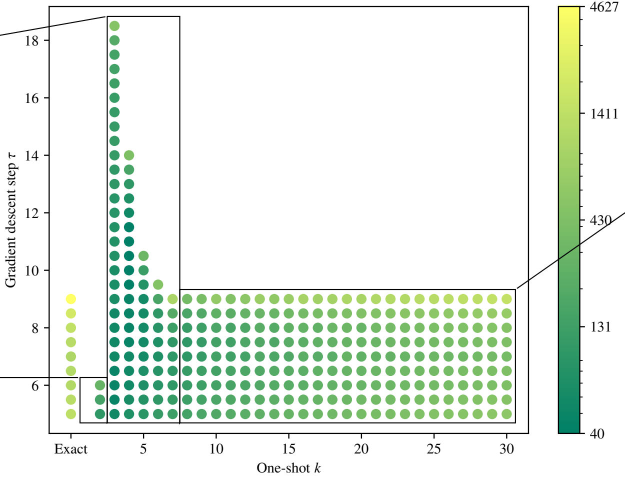

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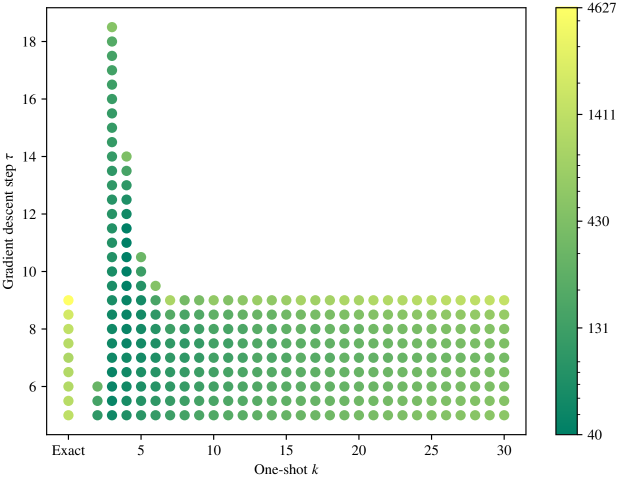
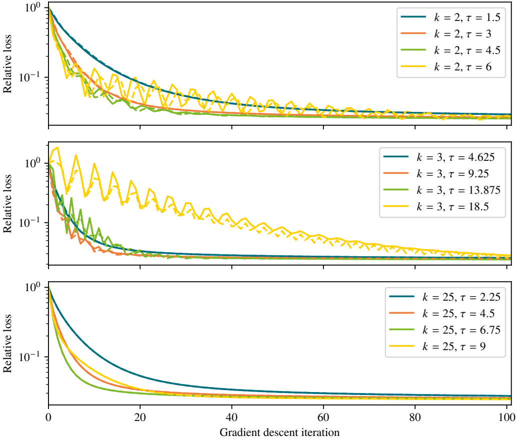
For a given step size τ, choosing an adequate value of k is **effective** at reducing the cost to reach convergence, even if this value is within the intermediate range



Stationary iteration: relative loss

The behavior relative loss $J(\delta u(\delta m))$ is monitored as τ approaches its maximal allowable value for a given k

- For $k = 25$, the convergence remains monotonous as τ approaches $\tau_{\max}$



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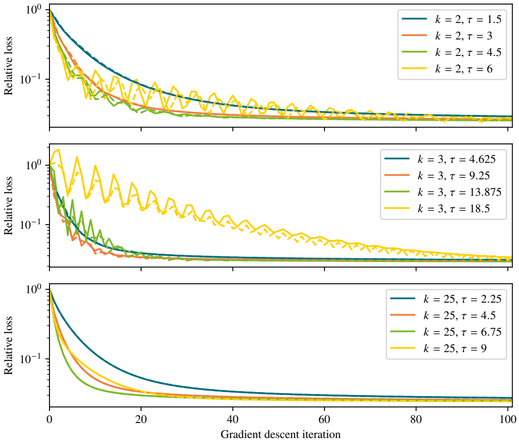

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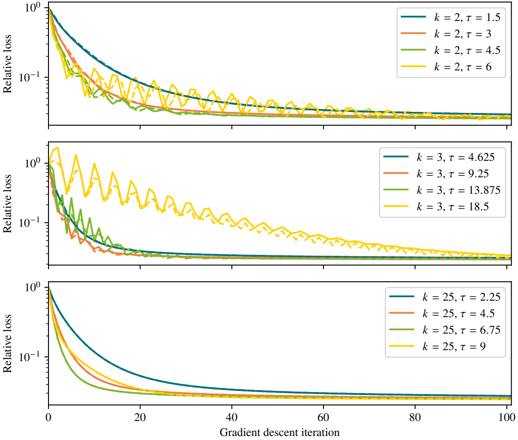

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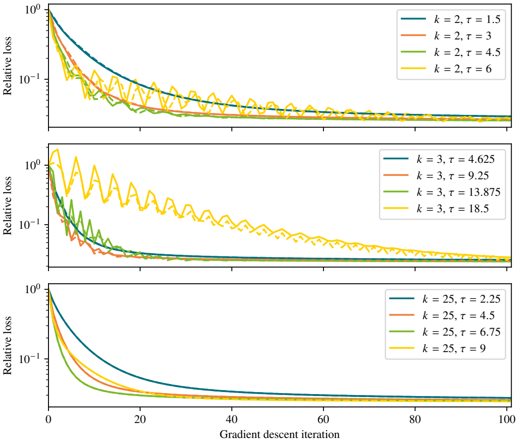
Overall, one-shot "loosens" the limit between monotonous convergence and diverging oscillations by facilitating **oscillating convergent** behaviors



Stationary iteration: gradient evolution with k (I)

To obtain an intuitive understanding, we compare the k-step one-shot estimated gradient g is compared to the LU-computed reference gradient g_{ref}

- 100 k-step one-shot **gradient descent iterations** with a **direct forward & adjoint solver** for a given τ

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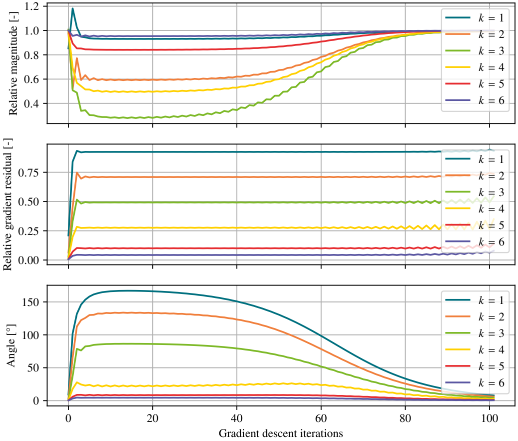
- This one-shot gradient is compared in **relative magnitude**, **angle**, and **relative difference** with the reference LU gradient

Stationary iteration: gradient evolution with k (II)

This experiment is performed on the linearized inverse problem at $1\,\text{Hz}$ using the Marmousi case (8 subdomains, METIS) for $\tau = 9$

- As k increases, the **angle** between the estimated and reference gradients **monotonously decreases**



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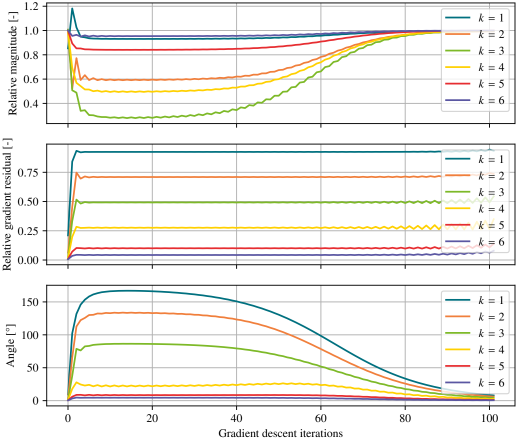

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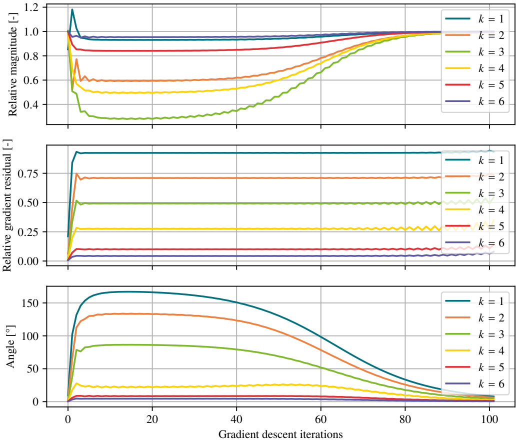
- The relative gradient difference is **roughly constant** for a given k



Adaptive step one-shot

Barzilai-Borwein method

Step size adaptivity for the descent can be implemented with the **Barzilai-Borwein** method

- The method introduces a **short** and a **long** step size

$$p^n_{\text{short}} = -\frac{\langle \Delta\delta m, \Delta g \rangle}{\langle \Delta g, \Delta g \rangle} g^n \quad \text{and} \quad p^n_{\text{long}} = -\frac{\langle \Delta\delta m, \Delta\delta m \rangle}{\langle \Delta\delta m, \Delta g \rangle} g^n$$

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- The geometric **mean** of the long and short step size is also useful in non-convex scenarios

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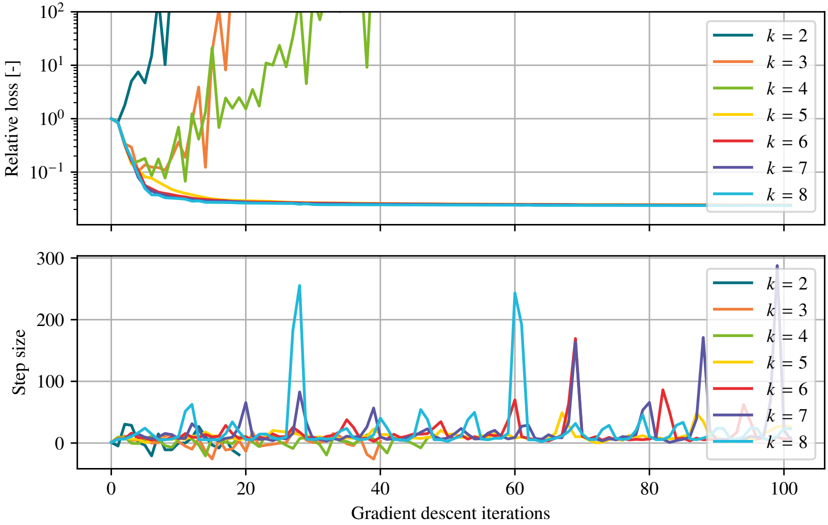
- For minimization of convex functionals, the short and long step sizes converge, albeit non-monotonously (Raydan, 1991)

Barzilai-Borwein: short step relative losses

The short and mean step sizes were found to be robust to the one-shot estimated gradients



Adaptive k one-shot

Negative step ramp-up

Requirement that the Barzilai-Borwein step size be positive. A strategy to upgrade k is therefore to

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Requirement that the Barzilai-Borwein step size be positive. A strategy to upgrade k is therefore to

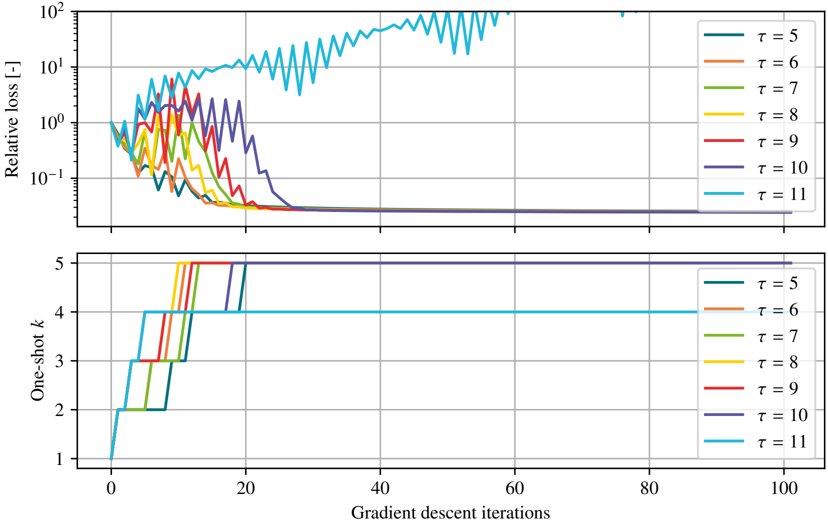
- Set k to an initial value of k_0
- Increase it every time the value of

$$\langle \Delta\delta m, \Delta g \rangle$$

is **negative**, as sampled by the one-shot estimated gradients

Negative step ramp-up: relative losses and k

This strategy was tested for the inversion of the linearized inverse problem at $1\,$Hz on the Marmousi model (8 subdomains, METIS) for various step sizes τ, with $k_0 = 1$



Non-linearized inverse problem

Gauss-Newton one-shot

The non-linearized inverse problem can be solved as a succession of linearized inverse problems using the Gauss-Newton method. A globalized scheme for the complete problem optimization becomes

1. Find the step direction p, the solution of the locally linearized problem

$$p = \arg\min_{\delta m} \tilde{J}(u(\delta m))$$

2. Find a scaling factor α that enforces the Armijo-Goldstein condition

$$J(u(m_k + \alpha p)) \leq J(u(m_k)) + c_1 D_m J(u(m_k))(\alpha p)$$

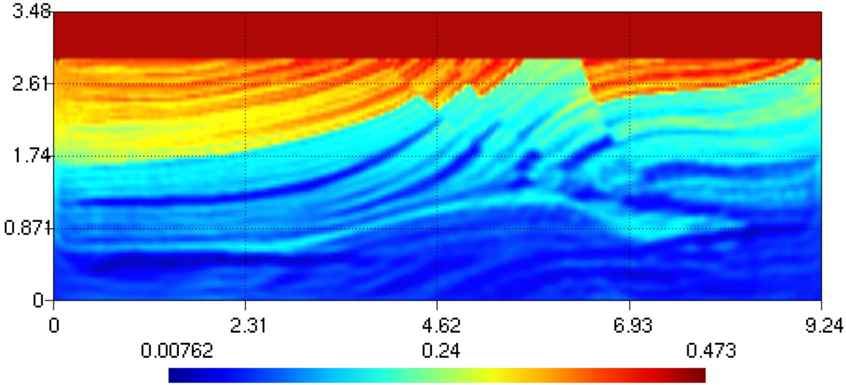
3. Update m such that

$$m_{k+1} = m_k + \alpha p$$

Step 1 may be done using one-shot gradient descent with adaptive step sizes and k schemes

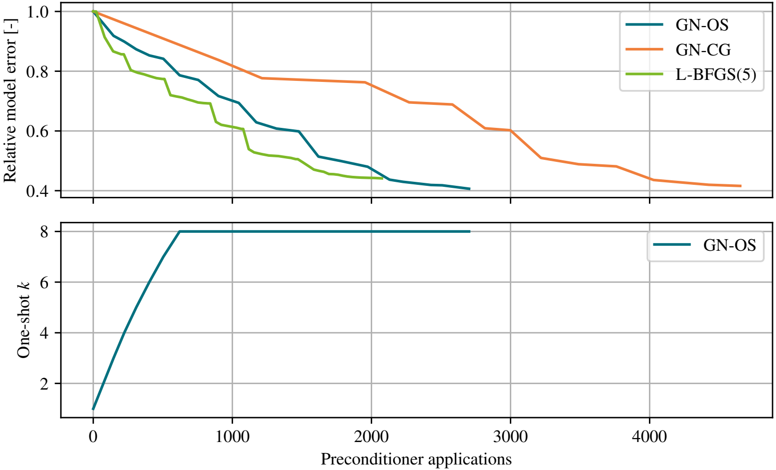
Test case 1: Marmousi (I)

This scheme was tested for the sequential inversion of the Marmousi case (Versteeg, 1994) at frequencies $\{1, 1.6, 2.5, 4, 6.5, 10.4\}$ Hz



Test case 1: Marmousi (II)

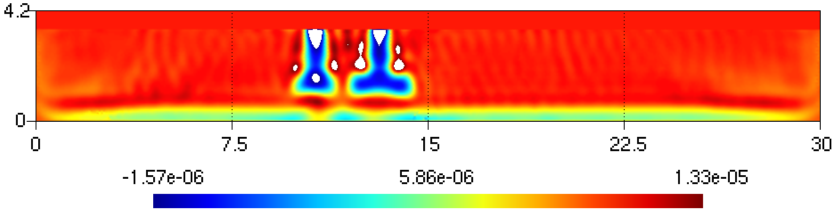
The inversion is compared with L-BFGS(5) and the Gauss-Newton-CG



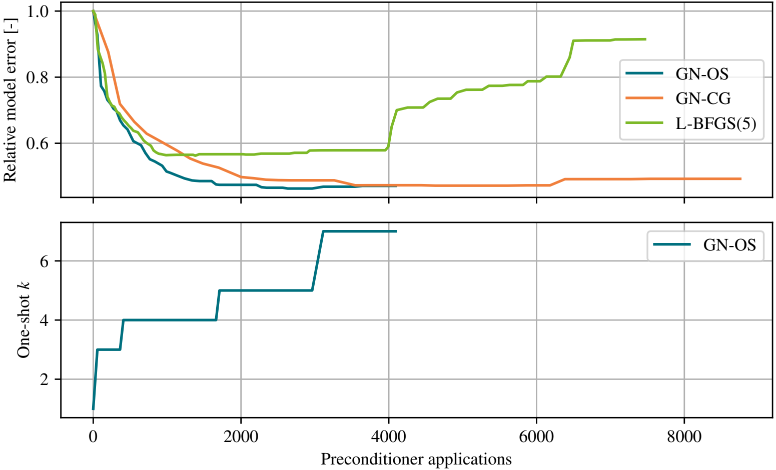
Using one-shot optimization to solve the Gauss-Newton equation leads to performances comparable to that of state-of-the-art algorithms

Test case 2: T-shaped reflectors (I)

This scheme was also tested for the inversion of near-surface imaging application consisting of T-shaped reflectors in a soil (Métivier et al., 2017) (with frequencies $\{100, 125, 150, 175, 200, 225, 250, 275, 300\}$ Hz)



Test case 2: T-shaped reflectors (II)



Conclusions & perspectives

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- Applying one-shot on the non-linearized problem remains to be explored
  - $\rightarrow$ No convexity guarantee
  - $\rightarrow$ Need a one-shot compatible globalization strategy
- The choice of an adequate k remains elusive

Contact

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Access my masters' thesis: