

# The Quadratic Wasserstein Metric for Earthquake Location

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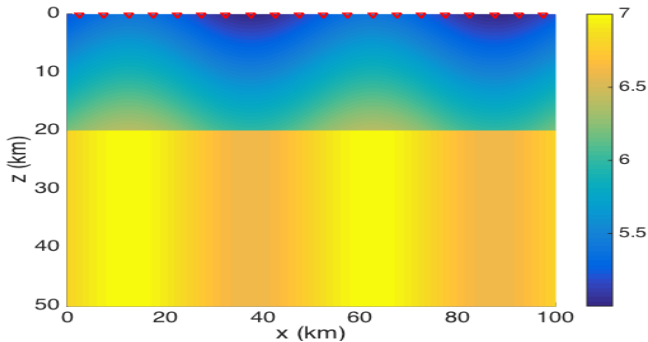
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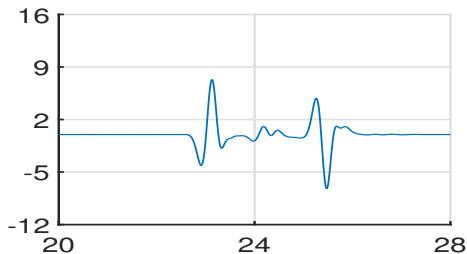
- twolayer model

$$c(x, z) = \begin{cases} 5.2 + 0.05z + 0.2 \sin(\pi x/25), & 0\text{km} \leq z \leq 20\text{km}, \\ 6.8 + 0.2 \sin(\pi x/25), & 20\text{km} < z \leq 40\text{km}. \end{cases}$$



red triangles indicate the receivers; total number:  $r$

- the earthquake happened at location  $\xi_T$  and time  $\tau_T$  (unknown)
- seismic signals  $g_i (1 \leq i \leq r)$  observed by the receivers (known)



- given  $\xi, \tau$ , we could compute the synthetic signals using PDE-based model

$$f_i = \mathcal{L}_i(\xi, \tau, c) \quad 1 \leq i \leq r$$

- optimization problem

$$(\xi^*, \tau^*) = \operatorname{argmin}_{\xi, \tau} \sum_{i=1}^r \mathbf{d}(f_i, g_i)$$

## Problems

- existence of local minima
- observed signals contain noise
- expensive PDE solving

## Previous work

- Prof. Engquist and Dr. Froese first used the Wasserstein metric to measure the misfit between seismic signals <sup>1</sup> in velocity structure inversion
- Dr. Métivier and collaborators proposed the KR norm based full waveform inversion <sup>2</sup>

## Our solutions

- **model** : square and normalize the signal and use Wasserstein metric to compare them
- **optimization** : use LMF algorithm to optimize with high efficiency

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<sup>1</sup>Engquist, Froese, and Yang [2016]

<sup>2</sup>Métivier, Brossier, Mérigot, Oudet, and Virieux [2017]

- for probability density functions  $\tilde{f}$ ,  $\tilde{g}$ , the quadratic Wasserstein metric

$$W_2^2(\tilde{f}, \tilde{g}) = \inf_{T \in \mathcal{M}} \int_{\mathbb{R}} |t - T(t)|^2 \tilde{f}(t) dt.$$

Set  $\mathcal{M}$  contains all the rearrange maps from  $\tilde{f}$  to  $\tilde{g}$ .

- for one dimension  $\tilde{f}, \tilde{g} : \mathbb{R} \rightarrow \mathbb{R}^+$

$$W_2^2(\tilde{f}, \tilde{g}) = \int_0^1 |F^{-1}(t) - G^{-1}(t)|^2 dt,$$

in which

$$F(t) = \int_{-\infty}^t \tilde{f}(\tau) d\tau, \quad G(t) = \int_{-\infty}^t \tilde{g}(\tau) d\tau.$$

- the optimal transport map

$$T(t) = G^{-1}(F(t)).$$

- our misfit function: for synthetic signal  $f$  and observed signal  $g$  supported in  $[0, t_f]$

$$\mathbf{d}(f, g) = W_2^2 \left( \frac{f^2}{\langle f^2 \rangle}, \frac{g^2}{\langle g^2 \rangle} \right)$$

- Fréchet gradient

$$\delta \mathbf{d} = \int_0^{t_f} 4(A(t) - B) f(t) \delta f(t) dt$$

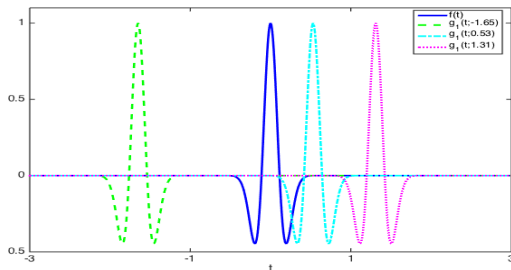
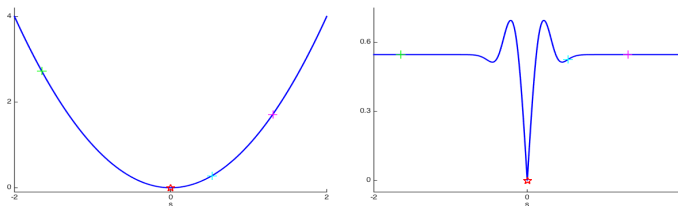
where

$$A(t) = \frac{\int_0^t (\tau - T(\tau)) d\tau}{\int_0^{t_f} f^2(t) dt}, \quad B = \frac{\int_0^{t_f} \left( \int_0^t (\tau - T(\tau)) d\tau \right) f^2(t) dt}{\left( \int_0^{t_f} f^2(t) dt \right)^2}$$

- apply adjoint method to obtain

$$\delta \mathbf{d} = K^\xi \cdot \delta \xi + K^\tau \cdot \delta \tau$$

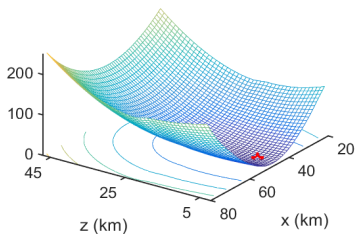
- time shift convexity

the signals  $f(t)$ ,  $g_i(t; s)$ distance  $d_i(s)$  (Left) and  $L^2$  difference  $\|f(t) - g_i(t; s)\|_2$  (Right)

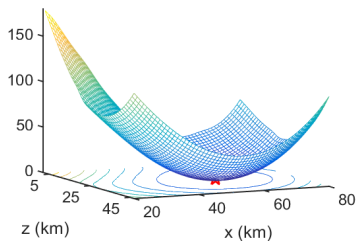


- convexity of our  $\sum_{i=1}^r \mathbf{d}(f_i(\xi, \tau_T, c), g_i)$  with respect to  $\xi$

shallow real location



deep real location



- quadratic structure and least-square formulation  $\rightarrow$  LMF algorithm

• inversion result

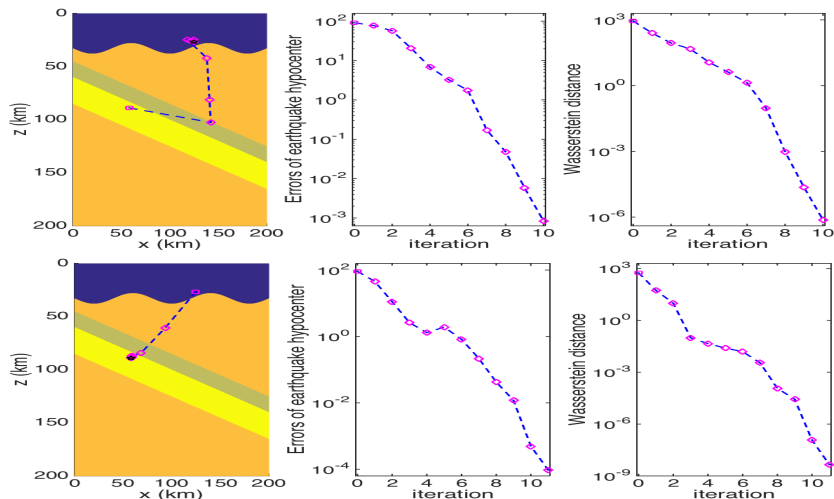


Figure: Convergence history of the subduction plate model

- noisy observed signal  $g_N(t)$  and real signal  $g$  on  $[0, t_f]$

$$g_N(t) = g(t) + r_N(t), \quad r_N(t) = r_j, \quad t \in \left(\frac{(j-1)t_f}{N}, \frac{jt_f}{N}\right], \quad (1 \leq j \leq N)$$

where  $r_j$  are i.i.d. random variables with  $\mathbb{E}r_j = 0$ ,  $\mathbb{D}r_j = \sigma^2$

- the redefined distance function:

$$\mathbf{d}_{\lambda(t)}(f, g_N) = W_2^2 \left( \frac{f^2 + \lambda}{\langle f^2 + \lambda \rangle}, \frac{g_N^2}{\langle g_N^2 \rangle} \right)$$

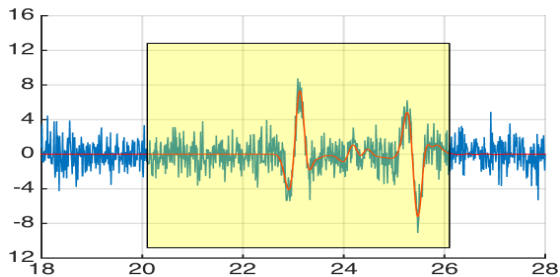
ideal choice  $\lambda(t) = \sigma^2$ , which leads to

$$\mathbb{E} \mathbf{d}_{\lambda}(g, g_N) = O\left(\frac{1}{N}\right)$$

- Comparison

$$\mathbb{E} \|g - g_N\|_{L^2} = O(1)$$

- noise



advantage of  $W_2$  metric in earthquake location problem

- promising convexity
- impact of data noise reduced
- fast convergence!

## References:

- Bjorn Engquist, Brittany D Froese, and Yunan Yang. Optimal transport for seismic full waveform inversion. 14(8), 2016.
- L. Métivier, R. Brossier, Q. Mérigot, E. Oudet, and J. Virieux. Measuring the misfit between seismograms using an optimal transport distance: application to full waveform inversion. *Geophysical Journal International*, 205(1):332–364, 2017.

Thanks for your attention!