

# A relaxed Beckmann's problem for SPD valued measures and application to Full Waveform Inversion

17/03/2023

Gabriele Todeschi

Labex Bézout, Université Gustave Eiffel

# Full Waveform Inversion (FWI)

**Objective:** reconstruct the velocity model  $v : D \subset \mathbb{R}^d \rightarrow \mathbb{R}_+$  of the acoustic wave equation

$$\frac{1}{v} \partial_t^2 p - \Delta p = s, \quad \text{in } [0, T] \times D$$

( $s$  source term)

# Full Waveform Inversion (FWI)

**Objective:** reconstruct the velocity model  $v : D \subset \mathbb{R}^d \rightarrow \mathbb{R}_+$  of the acoustic wave equation

$$\frac{1}{v} \partial_t^2 p - \Delta p = s, \quad \text{in } [0, T] \times D$$

( $s$  source term)

Variational problem:

$$v \in \underset{v}{\operatorname{arginf}} \mathcal{D}(d_{\text{pred}}[v], d_{\text{obs}}),$$

where  $\mathcal{D}$  is a misfit function between true measurements  $d_{\text{obs}}$  and predicted data  $d_{\text{pred}}[v]$ .

# Full Waveform Inversion (FWI)

**Objective:** reconstruct the velocity model  $v : D \subset \mathbb{R}^d \rightarrow \mathbb{R}_+$  of the acoustic wave equation

$$\frac{1}{v} \partial_t^2 p - \Delta p = s, \quad \text{in } [0, T] \times D$$

( $s$  source term)

Variational problem:

$$v \in \underset{v}{\operatorname{arg\,inf}} \mathcal{D}(d_{\text{pred}}[v], d_{\text{obs}}),$$

where  $\mathcal{D}$  is a misfit function between true measurements  $d_{\text{obs}}$  and predicted data  $d_{\text{pred}}[v]$ .

Measurements: pressure  $p(\cdot, x_r)$  or particles velocities  $u(\cdot, x_r) = (u_i(\cdot, x_r))_{i=1}^n$  for  $x_r \in D$ .

$D$  model space,  $\Omega = \{x_r, \dots, x_{N_r}\} \times [0, T]$  data space

# Full Waveform Inversion (FWI)

**Objective:** reconstruct the velocity model  $v : D \subset \mathbb{R}^d \rightarrow \mathbb{R}_+$  of the acoustic wave equation

$$\frac{1}{v} \partial_t^2 p - \Delta p = s, \quad \text{in } [0, T] \times D$$

( $s$  source term)

Variational problem:

$$v \in \underset{v}{\operatorname{arginf}} \mathcal{D}(d_{pred}[v], d_{obs}),$$

where  $\mathcal{D}$  is a misfit function between true measurements  $d_{obs}$  and predicted data  $d_{pred}[v]$ .

Measurements: pressure  $p(\cdot, x_r)$  or particles velocities  $u(\cdot, x_r) = (u_i(\cdot, x_r))_{i=1}^n$  for  $x_r \in D$ .

$D$  model space,  $\Omega = \{x_r, \dots, x_{N_r}\} \times [0, T]$  data space

The whole temporal evolution is used for the calibration  $\rightarrow$  **Full Waveform Inversion**

Highly non-convex problem (cycle skipping)

## Optimal transport misfit

Optimal transport can alleviate non-convexity

**Issue:** OT defined for probability measures  $\rightarrow$  need to handle the data

# Optimal transport misfit

Optimal transport can alleviate non-convexity

Issue: OT defined for probability measures  $\rightarrow$  need to handle the data

## Kantorovich-Rubenstein (KR) norm

For  $\mu, \nu \in \mathcal{M}(\Omega)$ ,  $\lambda \in \mathbb{R}_+$ :

$$KR(\mu, \nu) = \sup_{\phi} \left\{ \int_{\Omega} \phi(\mu - \nu), |\nabla \phi| \leq 1, |\phi| \leq \lambda \right\}$$

Optimal transport can alleviate non-convexity

Issue: OT defined for probability measures  $\rightarrow$  need to handle the data

## Kantorovich-Rubenstein (KR) norm

For  $\mu, \nu \in \mathcal{M}(\Omega)$ ,  $\lambda \in \mathbb{R}_+$ :

$$KR(\mu, \nu) = \sup_{\phi} \left\{ \int_{\Omega} \phi(\mu - \nu), |\nabla \phi| \leq 1, |\phi| \leq \lambda \right\}$$

"Relaxed" transport: if  $\mu, \nu \in \mathcal{P}(\Omega)$  and  $\lambda = +\infty \implies KR(\mu, \nu) = \mathcal{W}_1(\mu, \nu)$

$\mathcal{D} = KR(\mu, \nu)$  where  $\mu = d_{\text{pred}}[\nu]$ ,  $\nu = d_{\text{obs}} \rightarrow$  good results<sup>1</sup>

---

<sup>1</sup>Métivier et al., 2016



Optimal transport can alleviate non-convexity

Issue: OT defined for probability measures  $\rightarrow$  need to handle the data

## Kantorovich-Rubenstein (KR) norm

For  $\mu, \nu \in \mathcal{M}(\Omega)$ ,  $\lambda \in \mathbb{R}_+$ :

$$KR(\mu, \nu) = \sup_{\phi} \left\{ \int_{\Omega} \phi(\mu - \nu), |\nabla \phi| \leq 1, |\phi| \leq \lambda \right\}$$

"Relaxed" transport: if  $\mu, \nu \in \mathcal{P}(\Omega)$  and  $\lambda = +\infty \implies KR(\mu, \nu) = \mathcal{W}_1(\mu, \nu)$

$\mathcal{D} = KR(\mu, \nu)$  where  $\mu = d_{\text{pred}}[\nu]$ ,  $\nu = d_{\text{obs}}$   $\rightarrow$  good results<sup>1</sup>

If  $\int_{\Omega} \mu = \int_{\Omega} \nu$  and  $\lambda \gg 1$  then

$$KR(\mu, \nu) = KR((\mu - \nu)_+, (\mu - \nu)_-) = \mathcal{W}_1((\mu - \nu)_+, (\mu - \nu)_-)$$

$\implies$  **not convex** with respect to shifts

<sup>1</sup>Métivier et al., 2016

## Relaxed Beckmann's problem for SPD valued measures

Multi-component data  $u(\cdot, x_r)$  and  $L : \mathbb{R}^n \rightarrow \mathbb{S}_+^n$

## Relaxed Beckmann's problem for SPD valued measures

Multi-component data  $u(\cdot, x_r)$  and  $L : \mathbb{R}^n \rightarrow \mathbb{S}_+^n$

Pauli's transformation ( $d = 2$ ):

$$u = (u_x, u_z) \mapsto \begin{bmatrix} \alpha - u_x & u_z \\ u_z & \alpha + u_x \end{bmatrix}, \quad \text{with } \alpha = \sqrt{u_x^2 + u_z^2}.$$

## Relaxed Beckmann's problem for SPD valued measures

Multi-component data  $u(\cdot, x_r)$  and  $L : \mathbb{R}^n \rightarrow \mathbb{S}_+^n$

Pauli's transformation ( $d = 2$ ):

$$u = (u_x, u_z) \mapsto \begin{bmatrix} \alpha - u_x & u_z \\ u_z & \alpha + u_x \end{bmatrix}, \quad \text{with } \alpha = \sqrt{u_x^2 + u_z^2}.$$

$$\mu = L(u_{pred}[v]), \nu = L(u_{obs}[v]) \in \mathcal{M}(\Omega; \mathbb{S}_+^n)$$

# Relaxed Beckmann's problem for SPD valued measures

Multi-component data  $u(\cdot, x_r)$  and  $L : \mathbb{R}^n \rightarrow \mathbb{S}_+^n$

Pauli's transformation ( $d = 2$ ):

$$u = (u_x, u_z) \mapsto \begin{bmatrix} \alpha - u_x & u_z \\ u_z & \alpha + u_x \end{bmatrix}, \quad \text{with } \alpha = \sqrt{u_x^2 + u_z^2}.$$

$$\mu = L(u_{\text{pred}}[v]), \nu = L(u_{\text{obs}}[v]) \in \mathcal{M}(\Omega; \mathbb{S}_+^n)$$

## Relaxed Beckmann's problem

For  $\mu, \nu \in \mathcal{M}(\Omega; V_+)$ ,  $\lambda \in \mathbb{R}_+$ :

$$\inf_{\substack{\sigma \in \mathcal{M}(\Omega; V^n) \\ \delta \in \mathcal{M}(\Omega; V)}} \left\{ \int_{\Omega} |\sigma|_{V^d} + \lambda \int_{\Omega} |\delta|_V, \operatorname{div}_V(\sigma) = \mu - \nu + \delta \right\}$$

$$V = \mathbb{S}^n, V_+ = \mathbb{S}_+^n, V^d = [\mathbb{S}^n]^d,$$

$$|\cdot|_V \text{ Frobenius norm, } |\cdot|_{V^d} = \sum_{k=1}^d |\cdot|_V$$

$\operatorname{div}_V : \sigma \mapsto \sum_{i=k}^d \frac{\partial \sigma_k}{\partial x_k}$  and the constraint is to be considered in weak form

# Relaxed Beckmann's problem for SPD valued measures

Multi-component data  $u(\cdot, x_r)$  and  $L : \mathbb{R}^n \rightarrow \mathbb{S}_+^n$

Pauli's transformation ( $d = 2$ ):

$$u = (u_x, u_z) \mapsto \begin{bmatrix} \alpha - u_x & u_z \\ u_z & \alpha + u_x \end{bmatrix}, \quad \text{with } \alpha = \sqrt{u_x^2 + u_z^2}.$$

$$\mu = L(u_{pred}[v]), \nu = L(u_{obs}[v]) \in \mathcal{M}(\Omega; \mathbb{S}_+^n)$$

## Relaxed Beckmann's problem

For  $\mu, \nu \in \mathcal{M}(\Omega; V_+)$ ,  $\lambda \in \mathbb{R}_+$ :

$$\mathcal{T}_{p,q}^\lambda(\mu, \nu) = \inf_{\substack{\sigma \in \mathcal{M}(\Omega; V^n) \\ \delta \in \mathcal{M}(\Omega; V)}} \left\{ \frac{1}{p} \int_{\Omega} |\sigma|_{V^n}^p + \frac{\lambda}{q} \int_{\Omega} |\delta|_V^q, \operatorname{div}_V(\sigma) = \mu - \nu + \delta \right\}$$

$$V = \mathbb{S}^n, V_+ = \mathbb{S}_+^n, V^d = [\mathbb{S}^n]^d,$$

$$|\cdot|_V \text{ Frobenius norm, } |\cdot|_{V^d} = \sum_{k=1}^d |\cdot|_V$$

$\operatorname{div}_V : \sigma \mapsto \sum_{i=k}^d \frac{\partial \sigma_k}{\partial x_k}$  and the constraint is to be considered in weak form

**Remark:** the difference of mass can be quite big due to the difference of energy

# Tuning of the model

**Remark:** the difference of mass can be quite big due to the difference of energy

Choice of  $p, q \in \{1, 2\}$ :

- Sensitivity to (small) displacements (optimal transport problem)  $\longrightarrow p = 1$
- Penalization proportional to the energy of the signal  $\longrightarrow q = 2$



**Remark:** the difference of mass can be quite big due to the difference of energy

Choice of  $p, q \in \{1, 2\}$ :

- Sensitivity to (small) displacements (optimal transport problem)  $\longrightarrow p = 1$
- Penalization proportional to the energy of the signal  $\longrightarrow q = 2$

Choice of  $\lambda$ :

- For small values,  $\mathcal{T}_{p,q}^\lambda$  behaves like an  $L^q$  distance of  $\mu - \nu$
- For big values,  $\mathcal{T}_{p,q}^\lambda$  behaves like an  $L^q$  distance on "the mass difference"
- Dimensional analysis:

$$[\mu] = [\nu] = A, [\sigma] = A \cdot l \quad \longrightarrow \quad [\lambda] = A^{p-q} \cdot l^p$$

where  $l$  is a length,  $A$  an amplitude

## Duality results

Dual structure is useful for exact solutions, derivatives, numerical computation,...

## Duality results

Dual structure is useful for exact solutions, derivatives, numerical computation,...

$$p = 1, q = 1$$

$$\mathcal{T}_{1,1}^\lambda(\mu, \nu) = \sup_{\phi \in C(\Omega; V)} \left\{ \int \langle \phi, \nu - \mu \rangle_V, |\nabla \phi|_{V^n} \leq 1, |\phi|_V \leq \lambda \right\}$$

→ vectorial extension of the KR norm

## Duality results

Dual structure is useful for exact solutions, derivatives, numerical computation,...

$$p = 1, q = 1$$

$$\mathcal{T}_{1,1}^\lambda(\mu, \nu) = \sup_{\phi \in C(\Omega; V)} \left\{ \int \langle \phi, \nu - \mu \rangle_V, |\nabla \phi|_{V^n} \leq 1, |\phi|_V \leq \lambda \right\}$$

→ vectorial extension of the KR norm

$$p = 1, q = 2$$

$$\mathcal{T}_{1,2}^\lambda(\mu, \nu) = \sup_{\phi \in C(\Omega; V)} \left\{ \int_{\Omega} \langle \phi, \nu - \mu \rangle_V - \frac{1}{2\lambda} \int_{\Omega} |\phi|_V^2, |\nabla \phi|_{V^n} \leq 1 \right\}$$

→ quadratic penalization of the potential in the KR

## Duality results

Dual structure is useful for exact solutions, derivatives, numerical computation,...

$$p = 1, q = 1$$

$$\mathcal{T}_{1,1}^\lambda(\mu, \nu) = \sup_{\phi \in C(\Omega; V)} \left\{ \int \langle \phi, \nu - \mu \rangle_V, |\nabla \phi|_{V^n} \leq 1, |\phi|_V \leq \lambda \right\}$$

→ vectorial extension of the KR norm

$$p = 1, q = 2$$

$$\mathcal{T}_{1,2}^\lambda(\mu, \nu) = \sup_{\phi \in C(\Omega; V)} \left\{ \int_{\Omega} \langle \phi, \nu - \mu \rangle_V - \frac{1}{2\lambda} \int_{\Omega} |\phi|_V^2, |\nabla \phi|_{V^n} \leq 1 \right\}$$

→ quadratic penalization of the potential in the KR

$$p = 2, q = 2$$

$$\mathcal{T}_{2,2}^\lambda(\mu, \nu) = \sup_{\phi} -\frac{1}{2} \int_{\Omega} |\nabla \phi|_{V^n}^2 - \frac{1}{2\lambda} \int_{\Omega} |\phi|_V^2 + \int_{\Omega} \langle \phi, \nu - \mu \rangle_V$$

→ not a transport, not coupled...

## Exact solutions for $p = 1, q = 1$

Consider two delta measures  $\mu = M_1\delta_{x_1}, \nu = M_2\delta_{x_2}, M_1, M_2 \in \mathbb{S}_+^n$

## Exact solutions for $p = 1, q = 1$

Consider two delta measures  $\mu = M_1\delta_{x_1}, \nu = M_2\delta_{x_2}, M_1, M_2 \in \mathbb{S}_+^n$

→ (generalized) Fermat-Torricelli problem

## Exact solutions for $p = 1, q = 1$

Consider two delta measures  $\mu = M_1 \delta_{x_1}, \nu = M_2 \delta_{x_2}, M_1, M_2 \in \mathbb{S}_+^n$

→ (generalized) Fermat-Torricelli problem

The cost  $\mathcal{T}_{1,1}^\lambda(\mu, \nu)$  is equal to ( $\gamma = \frac{\lambda}{|x_1 - x_2|}$ )

$$\begin{cases} \lambda(|M_1|_V + |M_2|_V) & \text{if } 1 + \frac{\langle M_1, M_2 \rangle_V}{|M_1|_V |M_2|_V} \leq \frac{1}{2\gamma^2} \\ \lambda|M_1 - M_2|_V + |x_1 - x_2| |M_1|_V & \text{if } \frac{\langle M_1, M_1 - M_2 \rangle_V}{|M_1|_V |M_1 - M_2|_V} \leq -\frac{1}{2\gamma^2} \\ \lambda|M_1 - M_2|_V + |x_1 - x_2| |M_2|_V & \text{if } \frac{\langle M_2, M_2 - M_1 \rangle_V}{|M_2|_V |M_1 - M_2|_V} \leq -\frac{1}{2\gamma^2} \\ |x_1 - x_2| \left( \left( \gamma^2 - \frac{1}{2} \right) |M_1 - M_2|_V^2 + \frac{1}{2} (|M_1|_V^2 + |M_2|_V^2) + \right. \\ \quad \left. (4\gamma^2 - 1)^{\frac{1}{2}} (|M_1|_V^2 |M_2|_V^2 - \langle M_1, M_2 \rangle_V^2)^{\frac{1}{2}} \right)^{\frac{1}{2}} & \text{else.} \end{cases}$$



## Exact solutions for $p = 1, q = 1$

Consider two delta measures  $\mu = M_1\delta_{x_1}, \nu = M_2\delta_{x_2}, M_1, M_2 \in \mathbb{S}_+^n$

→ (generalized) Fermat-Torricelli problem

The cost  $\mathcal{T}_{1,1}^\lambda(\mu, \nu)$  is equal to ( $\gamma = \frac{\lambda}{|x_1 - x_2|}$ )

$$\begin{cases} \lambda(|M_1|_V + |M_2|_V) & \text{if } 1 + \frac{\langle M_1, M_2 \rangle_V}{|M_1|_V |M_2|_V} \leq \frac{1}{2\gamma^2} \\ \lambda|M_1 - M_2|_V + |x_1 - x_2||M_1|_V & \text{if } \frac{\langle M_1, M_1 - M_2 \rangle_V}{|M_1|_V |M_1 - M_2|_V} \leq -\frac{1}{2\gamma^2} \\ \lambda|M_1 - M_2|_V + |x_1 - x_2||M_2|_V & \text{if } \frac{\langle M_2, M_2 - M_1 \rangle_V}{|M_2|_V |M_1 - M_2|_V} \leq -\frac{1}{2\gamma^2} \\ |x_1 - x_2| \left( \left( \gamma^2 - \frac{1}{2} \right) |M_1 - M_2|_V^2 + \frac{1}{2} (|M_1|_V^2 + |M_2|_V^2) + \right. \\ \quad \left. (4\gamma^2 - 1)^{\frac{1}{2}} (|M_1|_V^2 |M_2|_V^2 - \langle M_1, M_2 \rangle_V^2)^{\frac{1}{2}} \right)^{\frac{1}{2}} & \text{else.} \end{cases}$$

$\gamma \leq \frac{1}{2} \implies$  the first condition is always met ( $M_1, M_2 \geq 0$ )

## Exact solutions for $p = 1, q = 1$

Consider two delta measures  $\mu = M_1\delta_{x_1}, \nu = M_2\delta_{x_2}, M_1, M_2 \in \mathbb{S}_+^n$

→ (generalized) Fermat-Torricelli problem

The cost  $\mathcal{T}_{1,1}^\lambda(\mu, \nu)$  is equal to ( $\gamma = \frac{\lambda}{|x_1 - x_2|}$ )

$$\begin{cases} \lambda(|M_1|_V + |M_2|_V) & \text{if } 1 + \frac{\langle M_1, M_2 \rangle_V}{|M_1|_V |M_2|_V} \leq \frac{1}{2\gamma^2} \\ \lambda|M_1 - M_2|_V + |x_1 - x_2||M_1|_V & \text{if } \frac{\langle M_1, M_1 - M_2 \rangle_V}{|M_1|_V |M_1 - M_2|_V} \leq -\frac{1}{2\gamma^2} \\ \lambda|M_1 - M_2|_V + |x_1 - x_2||M_2|_V & \text{if } \frac{\langle M_2, M_2 - M_1 \rangle_V}{|M_2|_V |M_1 - M_2|_V} \leq -\frac{1}{2\gamma^2} \\ |x_1 - x_2| \left( (\gamma^2 - \frac{1}{2})|M_1 - M_2|_V^2 + \frac{1}{2}(|M_1|_V^2 + |M_2|_V^2) + \right. \\ \quad \left. (4\gamma^2 - 1)^{\frac{1}{2}} (|M_1|_V^2 |M_2|_V^2 - \langle M_1, M_2 \rangle_V^2)^{\frac{1}{2}} \right)^{\frac{1}{2}} & \text{else.} \end{cases}$$

$\gamma \leq \frac{1}{2} \implies$  the first condition is always met ( $M_1, M_2 \geq 0$ )

→  $\lambda$  represents (half) the distance at which mass is transported

## Exact solutions for $p = 1, q = 2$

Consider two delta measures  $\mu = m_1\delta_{x_1}, \nu = m_2\delta_{x_2}, m_1, m_2 \in \mathbb{R}_+$

## Exact solutions for $p = 1, q = 2$

Consider two delta measures  $\mu = m_1\delta_{x_1}, \nu = m_2\delta_{x_2}, m_1, m_2 \in \mathbb{R}_+$

The optimal potential is:  $\phi(x_1) = a, \phi(x_2) = b$

$$\left\{ \begin{array}{l} a = \sqrt{\lambda(m_1 - m_2)}, b = a - |x_1 - x_2| \\ a = \frac{|x_1 - x_2|}{2} + \frac{\lambda(m_1 - m_2)}{2|x_1 - x_2|}, b = -\frac{|x_1 - x_2|}{2} + \frac{\lambda(m_1 - m_2)}{2|x_1 - x_2|} \\ a = \sqrt{\lambda m_1}, b = -\sqrt{\lambda m_2} \end{array} \right. \begin{array}{l} \text{if } \lambda \geq \frac{|x_1 - x_2|^2}{m_1 - m_2} \\ \text{and } m_1 \geq m_2 \\ \text{if } \lambda \leq \frac{|x_1 - x_2|^2}{|m_1 - m_2|} \\ \text{if } \lambda \leq \frac{|x_1 - x_2|^2}{(\sqrt{m_1} + \sqrt{m_2})^2} \end{array}$$

## Exact solutions for $p = 1, q = 2$

Consider two delta measures  $\mu = m_1\delta_{x_1}, \nu = m_2\delta_{x_2}, m_1, m_2 \in \mathbb{R}_+$

The optimal potential is:  $\phi(x_1) = a, \phi(x_2) = b$

$$\left\{ \begin{array}{l} a = \sqrt{\lambda(m_1 - m_2)}, b = a - |x_1 - x_2| \\ a = \frac{|x_1 - x_2|}{2} + \frac{\lambda(m_1 - m_2)}{2|x_1 - x_2|}, b = -\frac{|x_1 - x_2|}{2} + \frac{\lambda(m_1 - m_2)}{2|x_1 - x_2|} \\ a = \sqrt{\lambda m_1}, b = -\sqrt{\lambda m_2} \end{array} \right. \begin{array}{l} \text{if } \lambda \geq \frac{|x_1 - x_2|^2}{m_1 - m_2} \\ \text{and } m_1 \geq m_2 \\ \text{if } \lambda \leq \frac{|x_1 - x_2|^2}{|m_1 - m_2|} \\ \text{if } \lambda \leq \frac{|x_1 - x_2|^2}{(\sqrt{m_1} + \sqrt{m_2})^2} \end{array}$$

→  $\lambda$  represents the distance at which a unit of mass is transported

## Exact solutions for $p = 1, q = 2$

Consider two delta measures  $\mu = m_1\delta_{x_1}, \nu = m_2\delta_{x_2}, m_1, m_2 \in \mathbb{R}_+$

The optimal potential is:  $\phi(x_1) = a, \phi(x_2) = b$

$$\left\{ \begin{array}{l} a = \sqrt{\lambda(m_1 - m_2)}, b = a - |x_1 - x_2| \\ a = \frac{|x_1 - x_2|}{2} + \frac{\lambda(m_1 - m_2)}{2|x_1 - x_2|}, b = -\frac{|x_1 - x_2|}{2} + \frac{\lambda(m_1 - m_2)}{2|x_1 - x_2|} \\ a = \sqrt{\lambda m_1}, b = -\sqrt{\lambda m_2} \end{array} \right. \begin{array}{l} \text{if } \lambda \geq \frac{|x_1 - x_2|^2}{m_1 - m_2} \\ \text{and } m_1 \geq m_2 \\ \text{if } \lambda \leq \frac{|x_1 - x_2|^2}{|m_1 - m_2|} \\ \text{if } \lambda \leq \frac{|x_1 - x_2|^2}{(\sqrt{m_1} + \sqrt{m_2})^2} \end{array}$$

→  $\lambda$  represents the distance at which a unit of mass is transported

The tuning of  $\lambda$  can be done by choosing a reference transport distance and a reference mass to be transported

Numerical solution of  $\mathcal{T}_{p,q}^\lambda$ :

- Finite difference discretization
- SDMM algorithm: primal-dual proximal splitting technique
- Bottleneck: solution of a Poisson equation
- The SPD transport does not reflect on the complexity of the algorithm
- ( $p = 1, q = 2$ )  $\rightarrow$  the higher regularity can be exploited (FISTA, Chambolle-Pock, ...)

Numerical solution of  $\mathcal{T}_{p,q}^\lambda$ :

- Finite difference discretization
- SDMM algorithm: primal-dual proximal splitting technique
- Bottleneck: solution of a Poisson equation
- The SPD transport does not reflect on the complexity of the algorithm
- ( $p = 1, q = 2$ )  $\rightarrow$  the higher regularity can be exploited (FISTA, Chambolle-Pock, ...)

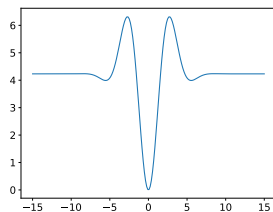
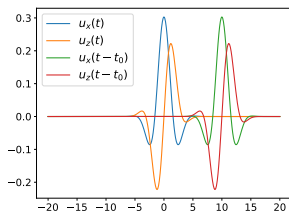
Solution of the inverse problem:

- I-BFGS algorithm: requires  $\frac{\partial \mathcal{D}(\mu[v], \nu)}{\partial v}$
- Derivative via adjoint state method: requires  $\frac{\partial \mathcal{T}_{p,q}^\lambda(\mu, \nu)}{\partial \mu}$
- thanks to the dual structure:

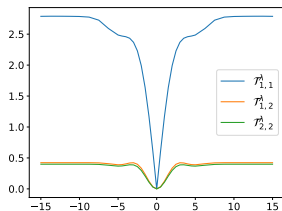
$$\frac{\partial \mathcal{T}_{p,q}^\lambda(\mu, \nu)}{\partial \mu} = \phi$$



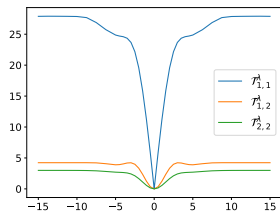
# Numerical results: sensitivity to time shift



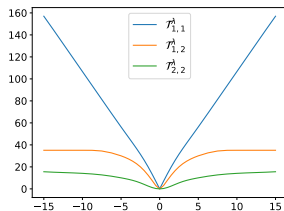
$L^2$  norm



$\lambda = 0.1$



$\lambda = 1$



$\lambda = 10$

## Numerical results: Marmousi test case

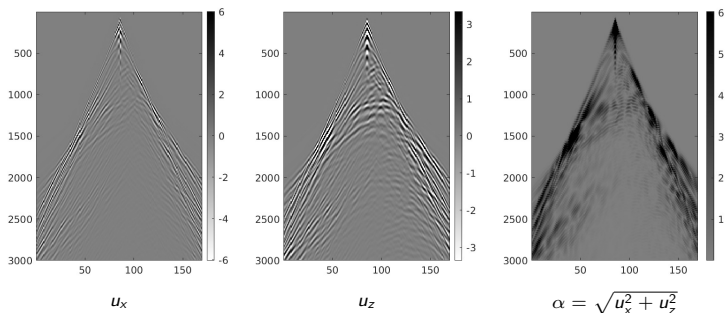
$$D = [a, b] \times [c, d] \subset \mathbb{R}^2, n = 2, T = 3000, N_r = 169$$

$$\Omega = \{x_1, \dots, x_{N_r}\} \times [0, T] \text{ semi-discrete 2d domain}$$

## Numerical results: Marmousi test case

$$D = [a, b] \times [c, d] \subset \mathbb{R}^2, n = 2, T = 3000, N_r = 169$$

$\Omega = \{x_1, \dots, x_{N_r}\} \times [0, T]$  semi-discrete 2d domain

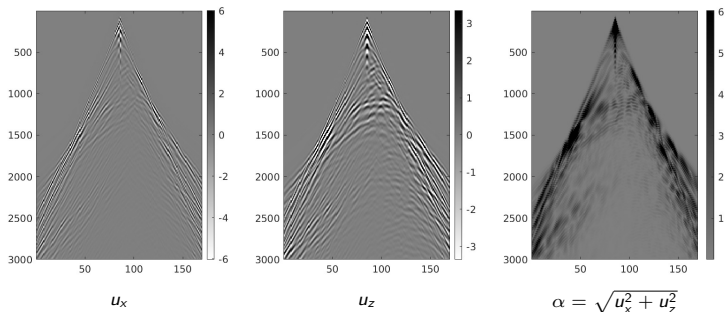


"Dimensional anisotropy":  $\tilde{\Omega} = \{x_r, \dots, x_{N_r}\} \times [0, T/\bar{v}]$  where  $\bar{v}$  mean velocity

## Numerical results: Marmousi test case

$$D = [a, b] \times [c, d] \subset \mathbb{R}^2, n = 2, T = 3000, N_r = 169$$

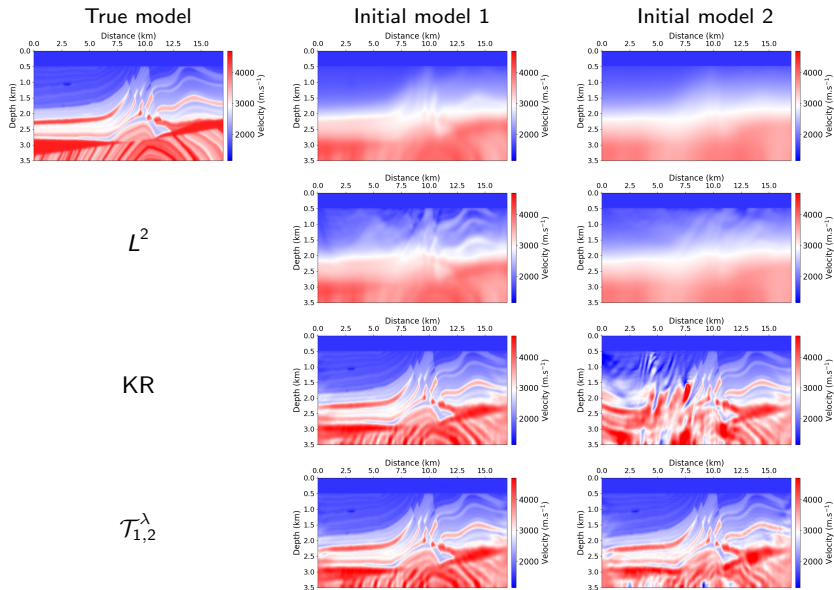
$\Omega = \{x_1, \dots, x_{N_r}\} \times [0, T]$  semi-discrete 2d domain



"Dimensional anisotropy":  $\tilde{\Omega} = \{x_r, \dots, x_{N_r}\} \times [0, T/\bar{v}]$  where  $\bar{v}$  mean velocity

For  $(p = 1, q = 1)$ ,  $\lambda \approx \frac{fq}{2\bar{v}}$ ; for  $(p = 1, q = 2)$ ,  $\lambda \approx \frac{fq}{2\bar{v}10^{-4}}$ ;  $fq$ : frequency of  $s$

# Numerical results: Marmousi test case



We introduced an (unbalanced) L1 transport for SPD valued measures to transport multi-component signals

Computationally affordable

Good results for the FWI problem justifying the approach

Applications to other problems can be foreseen

We introduced an (unbalanced) L1 transport for SPD valued measures to transport multi-component signals

Computationally affordable

Good results for the FWI problem justifying the approach

Applications to other problems can be foreseen

BUT:

- Rely on a lift function: linked to the physics of the problem at hand
- Sensitivity to the calibration of  $\lambda$  (depending again on the lift/physics)

Thank you for your attention!