Regularization for seismic sources inversion from interferometric data

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General model



General model



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Frequency

$$\begin{cases} \Delta u(\mathbf{r},\omega) + \frac{\omega^2}{c^2(\mathbf{r})} u(\mathbf{r},\omega) = -s(\mathbf{r}), & \mathbf{r} \in \mathbb{R}^d, & t \in [0,+\infty) \\ \text{outgoing condition in } \mathbb{R}^d \end{cases}$$

Interferomtric data (time)



Linear inversion problem:

Find the source $s(\mathbf{r})$ from the knowledge of all $d_k(\omega)$.

Time Interferometric Data (cross-correlations)

$$D_{k\ell}(au) := \int_{\mathbb{R}} U(\mathbf{r}_k, t) U(\mathbf{r}_\ell, t - au) dt, \quad t \in [0, +\infty)$$

We call $d_k(\omega) := u(\mathbf{r}_k, \omega)$ then

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Frequency Interferometric Data

$$\mathsf{D}_{k\ell}(\omega):=\mathsf{d}_k(\omega)\overline{\mathsf{d}_\ell}(\omega),\,\,\omega\in[0,+\infty)$$

and more generally

$$D_{k\ell}(\omega,\omega') := d_k(\omega)\overline{d_\ell}(\omega'), \quad \omega,\omega' \in [0,+\infty).$$

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How these data can be used to increase stability?

Interferomtric source inversion problem



Interferometric inversion problem:

Find the source $s(\mathbf{r})$ from the knowledge of some $D_{k\ell}(\omega, \omega') := d_k(\omega)\overline{d_\ell}(\omega')$.

- Advantage of interferometric data
- Coherent Interferometric imaging (back propagation)
- Non convex interferometric inversion
- Regularization is needed
- Algorithm for non convex descent
- Numerical exemples

Under far field approximation, and with constant wave speed c_0

$$d_k^{\mathsf{ex}}(\omega) := u^{\mathsf{ex}}(\mathbf{r}_k, \omega) = G_{\omega}^{\mathsf{ex}}(\mathbf{r}_k) \hat{s}\left(\frac{\omega}{c_0} \frac{\mathbf{r}_k}{|\mathbf{r}_k|}\right)$$

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$$G^{\mathsf{ex}}_{\omega}(\mathbf{r}_k) := rac{e^{rac{i\omega}{c_0}|\mathbf{r}_k|}}{4\pi|\mathbf{r}_k|}.$$

Smooth uncertainties over wavespeed leads at first order to an error on the travel time:

$$\tau_k := \frac{1}{c_0} |\mathbf{r}_k| + \varphi_k.$$

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In general,

- φ_k is not small (to compare to $2\pi/\omega$) \Rightarrow linear inversion fails!
- φ_k is smooth ($\varphi_k \approx \varphi_{k+1}$).

Phase uncertainties



Figure: Phase uncertainty on the receivers/frequencies domain.

Why interferometric data are interesting?

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Available interferometric data

$$d_k(\omega)\overline{d_\ell}(\omega') = d_k^{\mathsf{ex}}(\omega)\overline{d_\ell^{\mathsf{ex}}}(\omega')e^{i(\omega\varphi_k - \omega'\varphi_\ell)}$$

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One can choose receivers k, ℓ and frequencies ω and ω' such that

$$|\omega\varphi_k - \omega'\varphi_\ell| \le \varepsilon$$

for ε small. Then

$$d_k(\omega)\overline{d_\ell}(\omega') \approx d_k^{\text{ex}}(\omega)\overline{d_\ell^{\text{ex}}}(\omega').$$

Borcea, Garnier, Papanicolaou, Tsogka:

$$I_{\Delta_{\omega},\Delta_{x}}^{CINT}(\mathbf{r}) := \int_{|\omega-\omega'|<\Delta_{\omega}} \sum_{|\mathbf{r}_{k}-\mathbf{r}_{\ell}|<\Delta_{x}} \overline{G_{\omega}}(\mathbf{r}-\mathbf{r}_{k})d_{k}(\omega)G_{\omega'}(\mathbf{r}-\mathbf{r}_{\ell})\overline{d_{\ell}}(\omega')d\omega d\omega'.$$

Imaging formed by back propagation applied on interferometric data for close-by frequencies and receivers.

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Imaging formed by back propagation applied on interferometric data for close-by frequencies and receivers.

- It forms a smoothed version of the exact source.
- Resistant to random medium noise (wavespeed uncertainties)
- Difficult setting of $\Delta_{\omega}, \Delta_x$. To small \Rightarrow to smooth, To large \Rightarrow defocusing.

Classic linear inversion

After discretization of the source $x \in \mathbb{C}^n$, and the frequencies,

Discrete linear problem

Find $x \in \mathbb{C}^n$ s.t. Ax = b $b \in \mathbb{C}^p$.

where the forward operator matrix $A \in \mathbb{C}^{pn}$ is such that

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$$(Ax)_k := G_{\omega_k}^{\mathrm{ex}}(\mathbf{r}_k) \mathcal{F}x\left(\frac{\omega_k}{c_0} \frac{\mathbf{r}_k}{|\mathbf{r}_k|}\right), \quad \forall x \in \mathbb{C}^n.$$

and

$$b_{k}^{\mathsf{ex}} := G_{\omega_{k}}^{\mathsf{ex}}(\mathbf{r}_{k}) \mathcal{F} x^{\mathsf{ex}} \left(\frac{\omega_{k}}{c_{0}} \frac{\mathbf{r}_{k}}{|\mathbf{r}_{k}|} \right)$$
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- *b* − *b*^{ex} is not small.

 \Rightarrow solution $x^{LS} = A^{-1}b$ is a bad solution $(x^{LS} - x^{ex} \text{ is large})$.

Numerics LS



For all $x \in \mathbb{C}^n$, call $x^* := \overline{x}^T$.

$$Ax = b \quad \Rightarrow \quad Ax(Ax)^* = bb^*.$$

 bb^* is the inferometric data matrix. We only want to consider products $b_k \overline{b_\ell}$ with $|k - \ell|$ small.

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Selector matrix

 $E \in \mathcal{S}_n(\{0,1\})$ we denote $E(bb^*) := E_{k\ell} b_k \overline{b_\ell},$

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• Case E = 1 is eq. to Ax = b. (up to a multiplication by $e^{i\theta}$).

Least squares cost functional

$$x^{LS} := \arg \min J^{LS}(x), \quad J^{LS}(x) := \|Ax - b\|_2^2.$$

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Interferometric cost functional

$$\begin{split} x^{\text{int}} \in \arg\min J_E^{\text{int}}(x), \quad J_E^{\text{int}}(x) &:= |Ax(Ax)^* - bb^*|_E^2. \end{split}$$
 where $|M|_E^2 := \sum_{k\ell} E_{k\ell} |M_{k\ell}|^2.$

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- Are these two problems equivalent ?
- What's the influence of the selector matrix *E* on the solutions?
- Is the second problem numerically solvable?

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- Are these two problems equivalent ?
- What's the influence of the selector matrix *E* on the solutions?
- Is the second problem numerically solvable?
- If x^{int} is a solution, then $e^{i\alpha}x^{\text{int}}$ is solution.
- x^{LS} is a global minimizer of J_E^{int} .

Graph laplacian matrix

Take $E \in S_n(\{0,1\})$, the graph laplatian matrix of E is the matrix

$$(\Delta_E)_{ii} := \sum_{j
eq i} E_{ij}$$
 and $(\Delta_E)_{ij} := -E_{ij}$ for $i
eq j$.

 Δ_E is symetric positive semi-definite and $\lambda_1(\Delta_E) = 0$ and $\lambda_2(\Delta_E)$ measures the connection of the graph *E*.

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Theorem (Phase recovery from cross-products)

Consider $x \in \mathbb{C}^n$ such that $|x_k| = 1$ for all k. For any $x' \in \mathbb{C}^n$ satisfying $|x'_k| = 1$, there exists $\alpha \in [0, 2\pi)$ such that

$$\left\|x-e^{i\alpha}x'\right\|_{2} \leq \frac{\pi\sqrt{2}}{4\sqrt{\lambda_{2}(\Delta_{E})}}\left\|xx^{*}-x'x'^{*}\right\|_{E}.$$

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Idea for the proof:

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• If *E* is a connected graph, then $E_{k\ell}x_k\overline{x_\ell}$ contains enough phase differences to recover all phases up to a constant phase shift.

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- If *E* is a connected graph, then *E_{kℓ}x_kx_ℓ* contains enough phase differences to recover all phases up to a constant phase shift.
- The more *E* is a connected, the more this phase recovery is stable.

Data-graph laplacian and vector recovery 1

If the general case $x \in \mathbb{C}^n$, a similar result is possible. Problem: if $x_i = 0$ for some *i*, that can kill the connectivity between the phases.

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Data-graph laplacian

Take $E \in S_n(\{0,1\})$ and $x \in \mathbb{C}^n \setminus \{0\}$, the data-graph laplacian matrix of E is the matrix

$$\Delta_{E,|x|} := \operatorname{diag}(d) - S$$
 where $S_{ij} := E_{ij} \frac{|x_i|^2 |x_j|^2}{|xx^*|_F^2}$

and $d_i := \sum_j S_{ij}$. This matrix is also symmetric positive semi-definite.

 $\Delta_{E,|x|}$: is a weighted-graph laplacian.

Theorem (Vector recovery from cross-products) Consider $x \in \mathbb{C}^n$ and assume that for some $\eta > 0$, we have

$$\min_{k}(|x_{k}|) \geq \eta \left\|x\right\|_{2}.$$

For any $x' \in \mathbb{C}^n$ satisfying, there exists $\alpha \in [0, 2\pi)$ such that

$$\frac{\|x - e^{i\alpha}x'\|_2}{\|x\|_2} \le \left(\frac{\pi}{\sqrt{\lambda_2(\Delta_{E,|x|})}} + \frac{\sqrt{2}}{\eta}\right) \frac{|xx^* - x'x'^*|_E}{|xx^*|_E}.$$

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Consequence on the linear system Ax = b:

$$\|e^{i\alpha}Ax - b\|_2^2 \leq 2\left(\frac{\pi^2}{\lambda_2(\Delta_{E,|b|})} + \frac{2}{\eta^2}\right)|(Ax)(Ax)^* - bb^*|_E^2.$$

Corollary

If b satisfies $\min_k(|b_k|) \ge \eta \|b\|_2$, then for all $x \in \mathbb{C}^n$, $\exists \alpha \in [0, 2\pi)$

$$J^{LS}(e^{i\alpha}x) \leq \frac{2}{\|x\|_2^2} \left(\frac{\pi^2}{\lambda_2(\Delta_{E,|b|})} + \frac{2}{\eta^2}\right) J_E^{int}(x).$$

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Consequence: Under this hypothesis, the interferometric inversion is equivalent to the least squares inversion! Remember: that x^{LS} minimizes J_F^{int} .

What can be done?

We have the following situation :

Vectors x^{ex} and x^{LS} are very different and

$$\begin{split} J^{LS}(x^{LS}) &= 0 \qquad \qquad J^{\text{int}}_E(x^{LS}) = 0 \\ J^{LS}(x^{ex}) \text{ large} \qquad \qquad J^{\text{int}}_E(x^{ex}) < \varepsilon. \end{split}$$

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 \Rightarrow minimizing $J_E^{\rm int}$ is ill-posed. \Rightarrow a discrimination between x^{LS} and $x^{\rm ex}$ is needed.

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⇒ minimizing J_E^{int} is ill-posed. ⇒ a discrimination between x^{LS} and x^{ex} is needed. We numerically remark that, is x^{LS} is sparse then

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$$||x^{\mathsf{ex}}||_1 << ||x^{\mathsf{LS}}||_1.$$

 ℓ^1 -penalized interferometric inversion $x^{\text{int}} \in rg\min |Ax(Ax)^* - bb^*|_E^2 + \lambda ||x||_1.$

Algorithm

ℓ^1 -penalized interferometric inversion

$$x^{\mathsf{int}} \in rg\min|Ax(Ax)^* - bb^*|_E^2 + \lambda \|x\|_1$$

We use optimal step descent: $\nabla J_E^{int}(x) = A^* E(Axx^*A^* - bb^*)Ax$

- Initialize $x \in \mathbb{C}^n \setminus \{0\}$.
- Compute $g =
 abla J_E^{ ext{int}}(x) + \lambda (rac{x_i}{|x_i|})_{i=1}^n$
- Compute The order 4, polynomial $P(t) = J_E^{int}(x + tg)$.
- Solve

$$t^* = \arg\min_{t} P(t) + \lambda \left\| x + tg \right\|_1$$

- Iterate x = x + t*g
- Threshold $x_i = 0$ if $|x_i| < \varepsilon$.
- Loop.



Figure: Line 1: no noise, Line 2: max noise amplitude = 2.

We choose E tri diagonal.



Figure: Line 1: max noise amplitude = 4, Line 2: max noise amplitude = 8



Figure: Line 1: max noise amplitude = 16, Line 2: max noise amplitude = 32.



Figure: Line 1: max noise amplitude = 64, Line 2: max noise amplitude = 128.

Thank you for your attention!