GLOBAL SEISMIC TOMOGRAPHY USING SOLA-BACKUS-GILBERT INVERSION



Symposium – Collège de France (2021) Global scale seismic imaging and dynamics of the Earth's mantle

►► Introduction

- Global tomographic models differ (at least on short wavelengths)
- Interpreting physical processes based on models without accurate resolution and uncertainty analyses is a hazardous endeavor
- SOLA-Backus-Gilbert inversion can help building a new generation of models accompanied with resolution/uncertainty informations



►► Large scale, linear(ized) tomographic problems

General form:

$$d_i = \int K_i(\mathbf{r}) m(\mathbf{r}) d^3\mathbf{r} + n_i$$

▶ Global tomography: 10⁵−10⁶ data



>> Reviving Backus–Gilbert theory for seismic tomography

- Backus–Gilbert theory (1967, 68, 70) seeks to determine Optimally Localized Averages (OLA) over the continuous 'true' Earth model.
- What is the average value, and the attached uncertainty, of velocity anomalies within some localized volume in the Earth's interior?
- "[B-G] carefully avoids using any a priori information on the model parameters that could 'bias' the inferences to be drawn from the data." (Tarantola, 2006)



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b Backus–Gilbert tomography in a nutshell (1/3)

Linear tomographic problem: $d_i = \int K_i(\mathbf{r}) m(\mathbf{r}) d^3\mathbf{r} + n_i (N \text{ data})$ $\widehat{m}^{(k)} = \sum_{i=1}^{N} x_i^{(k)} d_i = \int \left(\sum_i x_i^{(k)} K_i(\mathbf{r}) \right) m(\mathbf{r}) d^3 \mathbf{r} + \sum_i x_i^{(k)} n_i$ averaging kernel $A^{(k)}(\mathbf{r})$ noise effect $\mathbf{P} \hat{m}^{(k)} \approx \int A^{(k)}(\mathbf{r}) m(\mathbf{r}) d^3\mathbf{r}$ $\underbrace{\sigma_{\hat{m}^{(k)}}}_{i} = \sqrt{\sum_{i} \left(x_{i}^{(k)} \sigma_{d_{i}} \right)^{2}}$ uncertainty local averaging receivers \ receivers $A^{(k)}(\mathbf{r}) = \sum x_i^{(k)} K_i(\mathbf{r})$ 'true' model slab $m(\mathbf{r})$ slab Averaging kernel 'true' model $4^{(k)}(r)$ Averaging query point $\mathbf{r}^{(k)}$ kernel $m(\mathbf{r})$ $A^{(k)}(\mathbf{r})$ Non-zero weighted data-sensitivity ray paths kernels K_i(r) (i.e., $x_i^{(k)} \neq 0$) query point sources

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►► Backus–Gilbert tomography in a nutshell (2/3)

- Trade-off: resolution vs uncertainty
- Resolving length relates to the size of averaging kernel $A^{(k)}$
- Uncertainty $\sigma_{\hat{m}^{(k)}}$ describes noise effect on local average $\hat{m}^{(k)}$



►► Backus–Gilbert tomography in a nutshell (3/3)

From a collection of local averages to a tomographic 'image'

 Model appraisal is not an easy task — in particular when local resolution (and uncertainty) differs from one point to another



SOLA-Backus-Gilbert tomography in a nutshell (1/4)

Specify a priori information on local model resolution

- ▶ Target form $T^{(k)}$ for averaging kernel $A^{(k)}$ (Pijpers & Thompson, 92)
- Different from specifying a priori information on the model itself!



SOLA-Backus-Gilbert tomography in a nutshell (2/4)

References:

Zaroli (2019, *GJI*)
Zaroli (2016, *GJI*)

Zaroli *et al.* (2017, *GRL*)

Continuous SOLA tomography Discrete SOLA tomography Discrete SOLA *vs* DLS tomography

Example:



SOLA-Backus-Gilbert tomography in a nutshell (3/4)



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SOLA-Backus-Gilbert tomography in a nutshell (4/4)



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\triangleright SOLA *vs* traditional DLS tomography (1/4)



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IDENTIFY and STATE STATE SOLA *vs* traditional DLS tomography (2/4)

- ► Generalized inverse ⇒ Resolution and Uncertainty
- SOLA is more efficient than DLS for computing generalized inverses



IDENTIFY and STATE STATE SOLA *vs* traditional DLS tomography (3/4)



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►► SOLA vs traditional DLS tomography (4/4)



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Image: Tomographic applications



Image: Second S

SOLA tomography provides a natural framework for 'quantitatively' testing geodynamic scenarios against tomographic models



Freissler*, Zaroli, Lambotte, Schuberth (2020)

►► Conclusion

SOLA–Backus–Gilbert tomography:

- Models with resolution and uncertainty informations
- Direct control on resolution/uncertainty
- Models can be free of averaging-bias effects, and fit the data
- Data-kernels can be fully exploited (if no model space discretization)
- Natural framework for tomographic–geodynamic comparisons



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►► Need for 'quantitative' comparisons of models...



Image Solution b Tuning SOLA tomographic inversions

• **Recipe** for target kernels, $T^{(k)}$, and trade-off parameters, $\eta^{(k)}$



►► Visualizing 'at a glance' local resolution



►► Interrogating SOLA models (first example)



►► Interrogating SOLA models (second example)



►► Interrogating SOLA models (third example)



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Synthetic retrodiction experiment (R. Freissler's PhD thesis)



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