

Challenges and opportunities in sparse wavefield inversion

Felix J. Herrmann

SLIM 

Seismic Laboratory for Imaging and Modeling
the University of British Columbia

Motivation

Many successful seismic algorithms are *data*-driven

- Surface-related Multiple Elimination (SRME)
- Estimation of Primaries by Sparse Inversion (EPSI)
- Interferometric deconvolution

Require

- *dense* matrix vector *multiplies*
- *full* (azimuth) sampling
- *memory* and *matvec* make *scaling* to 3-D very *challenging*
- certainly in the light of push for more & more data

Goals

Use *redundant* information residing in *multiple* reflections.

Exploit *data-space* transform-domain *sparsity* & *low rank* to

- ▶ *stabilize* wavefield *inversion*
- ▶ *reduce* system sizes & *mitigate* cross-talk

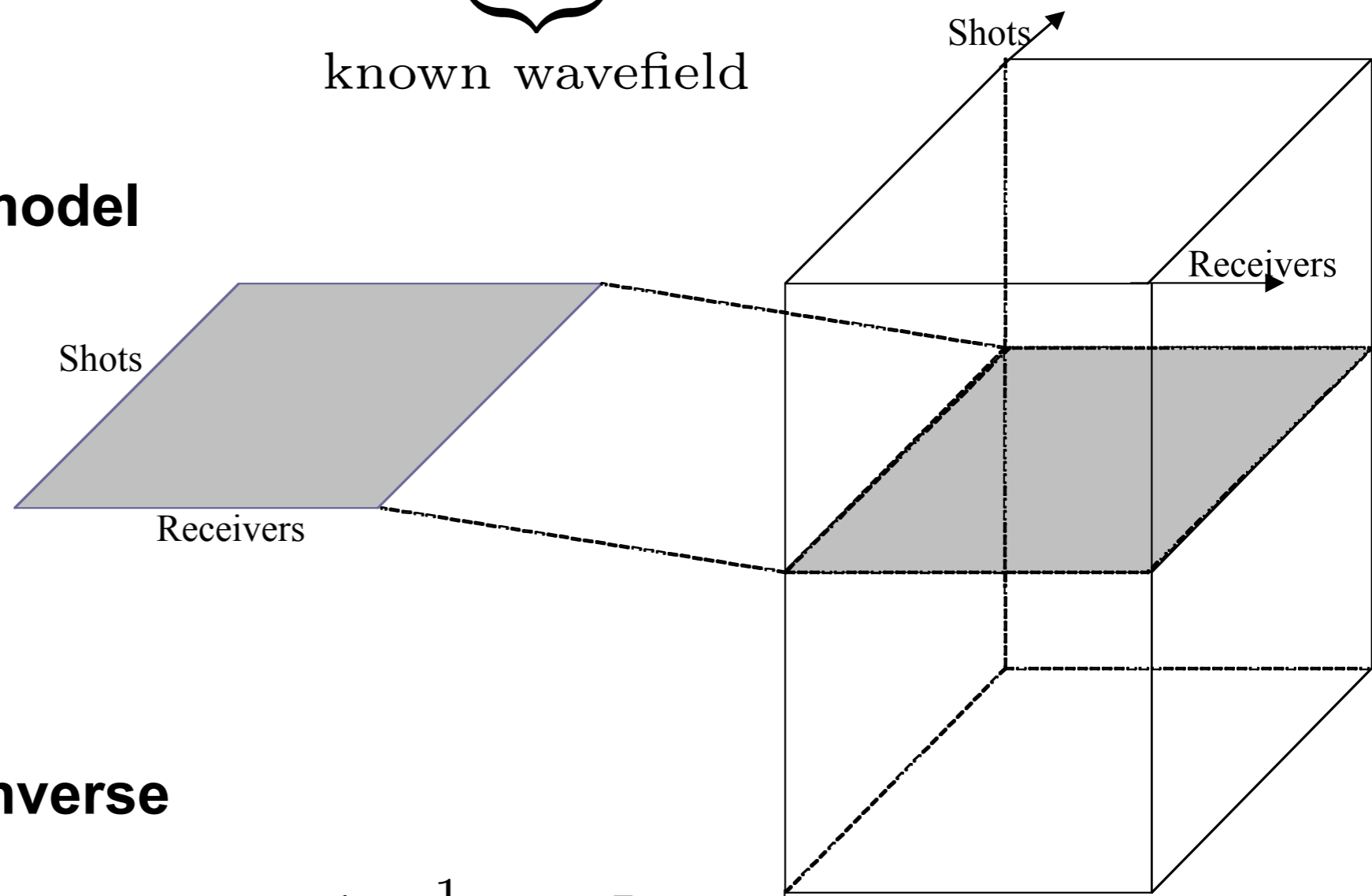
Exploit *adaptive model-space* transform-domain *sparsity* to

- ▶ *compute* *convolutions/correlations* via wave simulators
- ▶ *reduce* system sizes & *mitigate* cross-talk

“Typical” approach: damped least-squares

$$\underbrace{\hat{\mathbf{G}}_i}_{\text{unknown wavefield}} = \underbrace{\hat{\mathbf{U}}_i}_{\text{known wavefield}} \underbrace{\hat{\mathbf{V}}_i}_{\text{known wavefield}} \quad i = 1 \cdots n_f$$

Monochromatic forward model

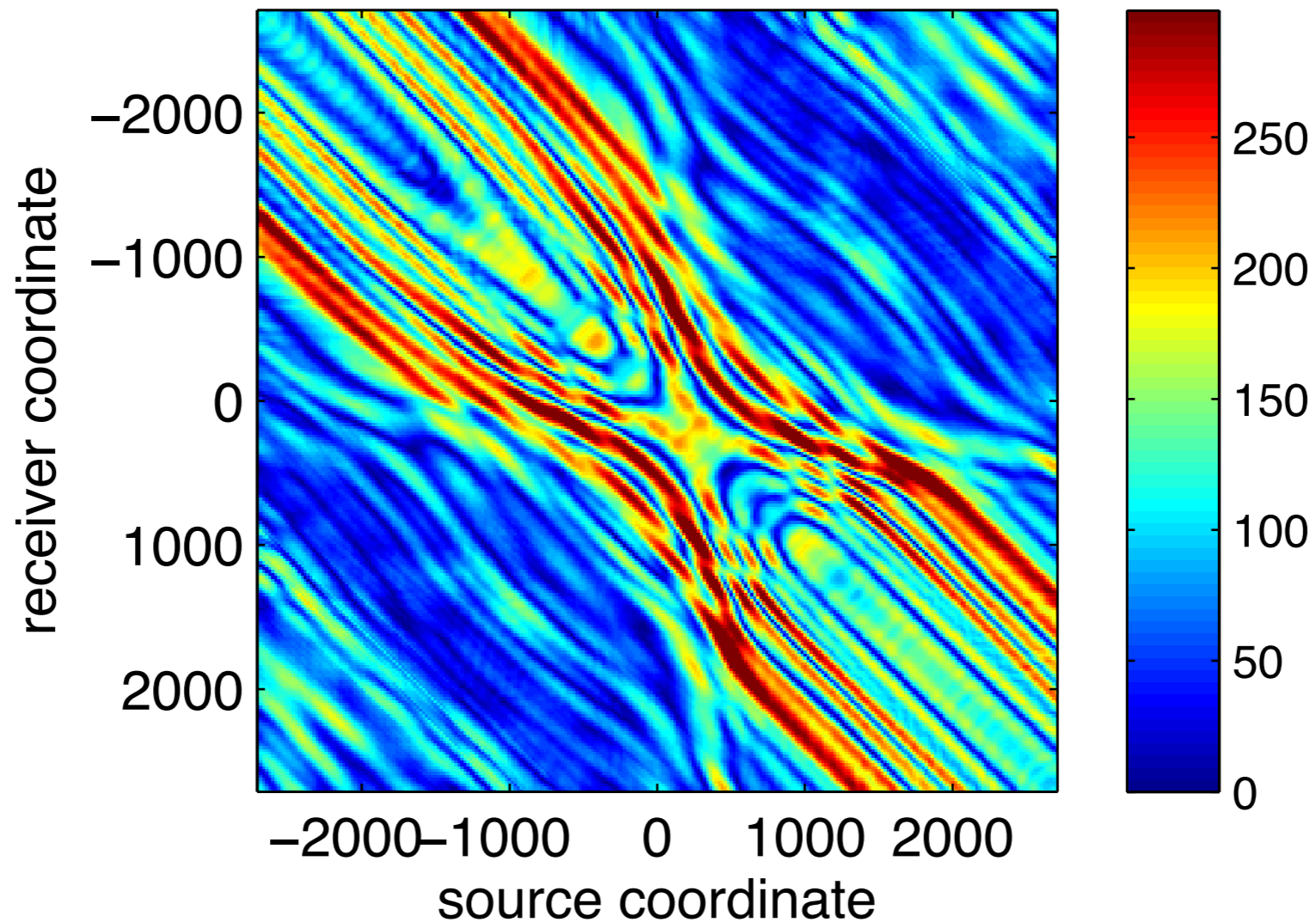


Monochromatic pseudo-inverse

$$\tilde{\hat{\mathbf{G}}}_i = \hat{\mathbf{V}}_i \hat{\mathbf{U}}_i^* \left(\hat{\mathbf{U}}_i \hat{\mathbf{U}}_i^* + \epsilon_i^2 \mathbf{I} \right)^{-1}, \quad i = 1 \cdots n_f,$$

[Berkhout '82]
[F.J.H '07-'08]
[Wapenaar '08]

Data matrix



- Inversion is carried out per frequency slice
- Water level leads to loss in resolution
- Can suffer from instabilities ...

Two- vs one-norms

Two-norm inversion:

- ▶ tends to *smooth* when *regularizing* the *null space*
- ▶ *ineffective* when *dealing* with *cross talk* induced by *randomized* sourcing (e.g., simultaneous)

One-norm *sparsity*-promoting inversion:

- ▶ leverages curvelet-domain *sparsity* of data
- ▶ highly *effective* for *removal* of source *crosstalk*
- ▶ *preserves* frequency *content*

Solutions

1. *Simultaneous* sourcing in *combination* with *renewals*
 - *reduces #* of shots & leverages *sparsity*-promoting solvers
2. *Wave-equation* based possibly in *combination* with 1.
 - leverages *sparse* wave simulators to carry our multi-D convolutions implicitly
3. Low-rank approximations
 - exploit multi-D structure of seismic wavefields

Randomized source encoding = compressive sensing

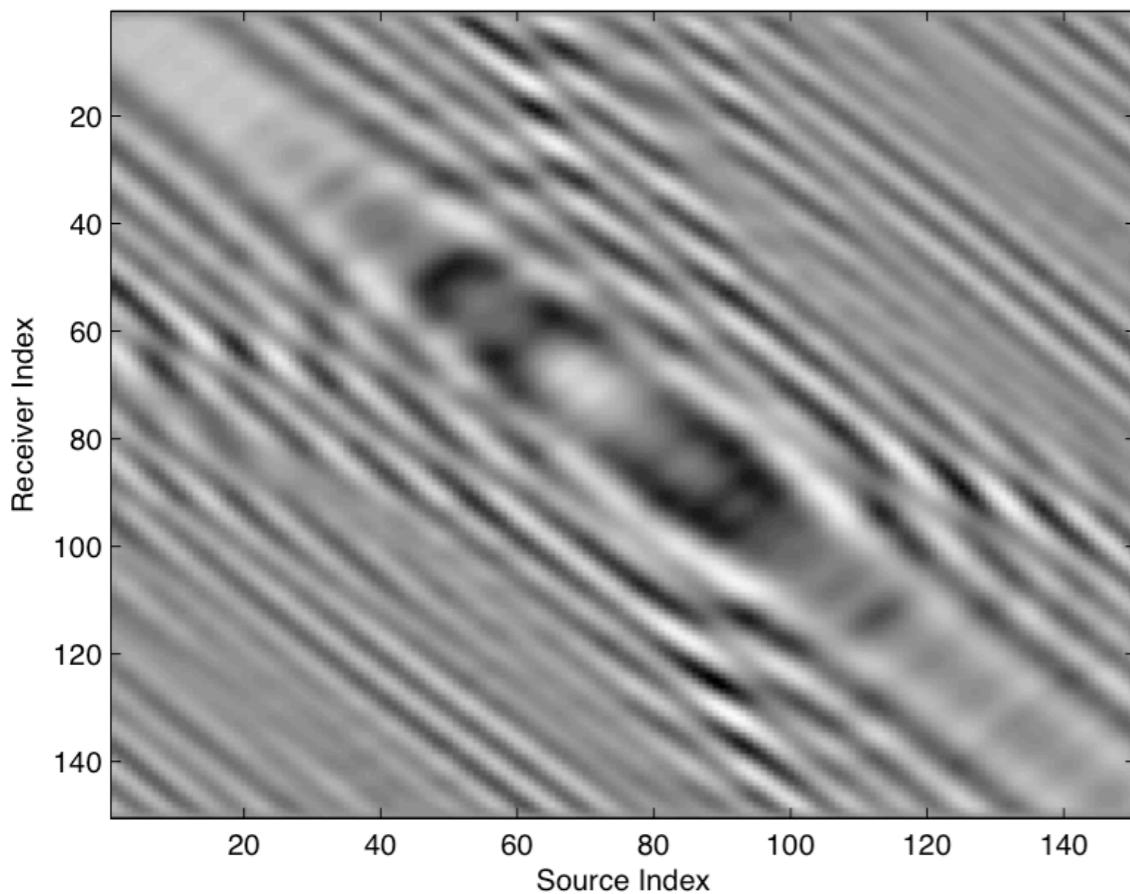
$$[\delta \mathbf{d}_1, \dots, \delta \mathbf{d}_{n_s}] \quad \mathbf{W} \quad [\underline{\delta \mathbf{d}}_1, \dots, \underline{\delta \mathbf{d}}_{n'_s}]$$

or

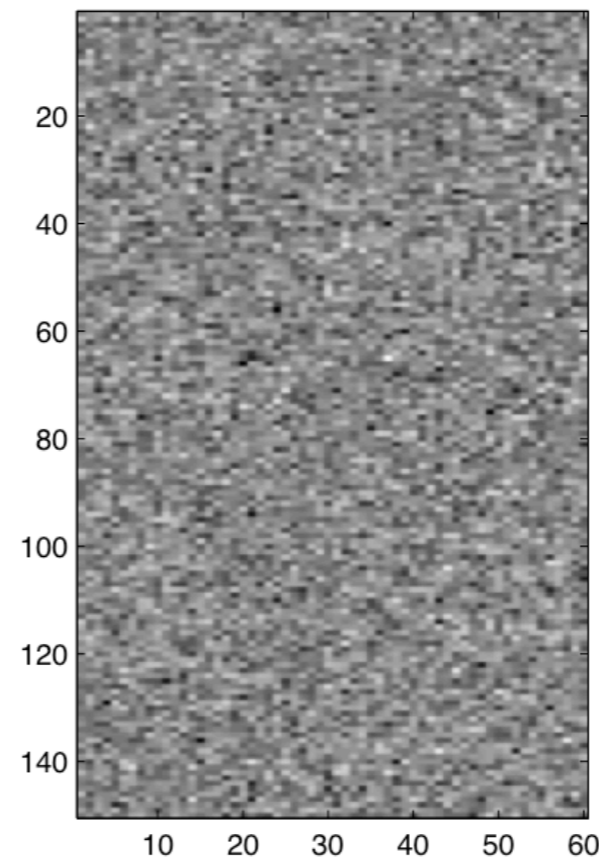
$$\left(\mathbf{W}^H \otimes \mathbf{I} \right) \text{vec}(\delta \mathbf{D}) = \text{vec}(\underline{\delta \mathbf{D}})$$

$$n'_s \ll n_s$$

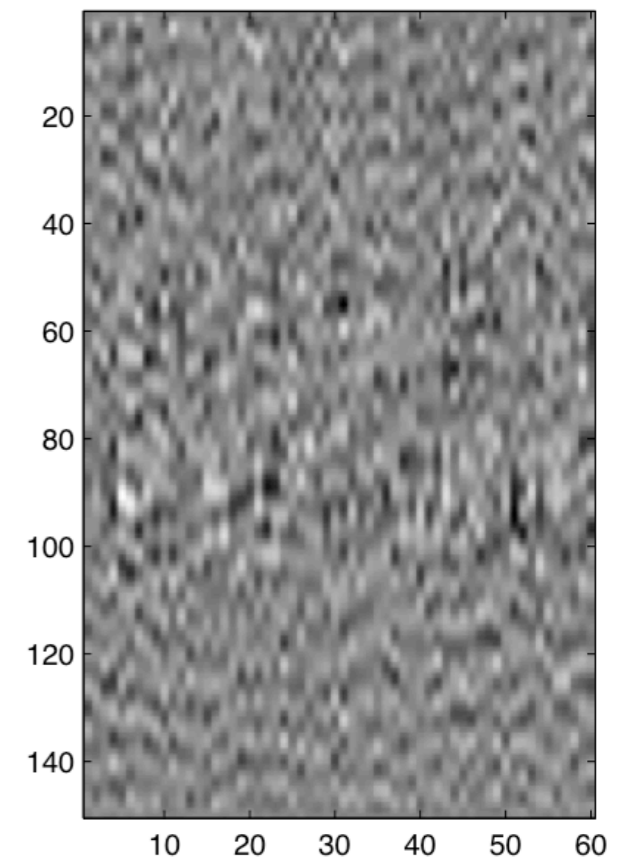
Source – Receiver Slice (Full Data)



Random Gaussian Matrix



Data * Random Gaussian Matrix



Approach I

Work with *simultaneous* sources, i.e.,

$$\hat{\mathbf{V}}\mathbf{W} = \hat{\mathbf{G}}\hat{\mathbf{U}}\mathbf{W} \quad \text{with} \quad \mathbf{W} \in \mathbb{C}^{n_s \times n'_s}, n'_s \ll n_s$$

- ▶ reduces system size but needs full acquisition for $\hat{\mathbf{U}}$
- ▶ could benefit from *redrawing* simultaneous shots
- ▶ $\hat{\mathbf{G}}$ is 'dense' & *redundant* in *sparsifying* domain
- ▶ still high matvec and storage costs

[Guitton, '02; Berkhout, '05; Whitmore '10; Ning et. al., '10-; Verschuur '11]

Approach II

Wave-equation based:

$$\hat{\mathbf{G}}\hat{\mathbf{U}} = \hat{\mathbf{F}}[\mathbf{m}, \hat{\mathbf{U}}]$$

with

$$\hat{\mathbf{F}}[\mathbf{m}, \hat{\mathbf{Q}}] = \mathbf{R}\hat{\mathbf{H}}^{-1}[\mathbf{m}]\mathbf{R}^*\hat{\mathbf{Q}}$$

yielding

$$\hat{\mathbf{F}}[\mathbf{m}, \mathbf{I}]\hat{\mathbf{U}} = \hat{\mathbf{F}}[\mathbf{m}, \hat{\mathbf{U}}]$$

Wave simulator does *heavy* lifting for the multi-D convolutions!

Approach II cont'd

After linearization for EPSI we have

$$\hat{\mathbf{P}} \approx \widehat{\nabla \mathbf{F}}[\mathbf{m}, \hat{\mathbf{Q}} - \hat{\mathbf{P}}] \delta \mathbf{m}$$

and *simultaneous* sourcing

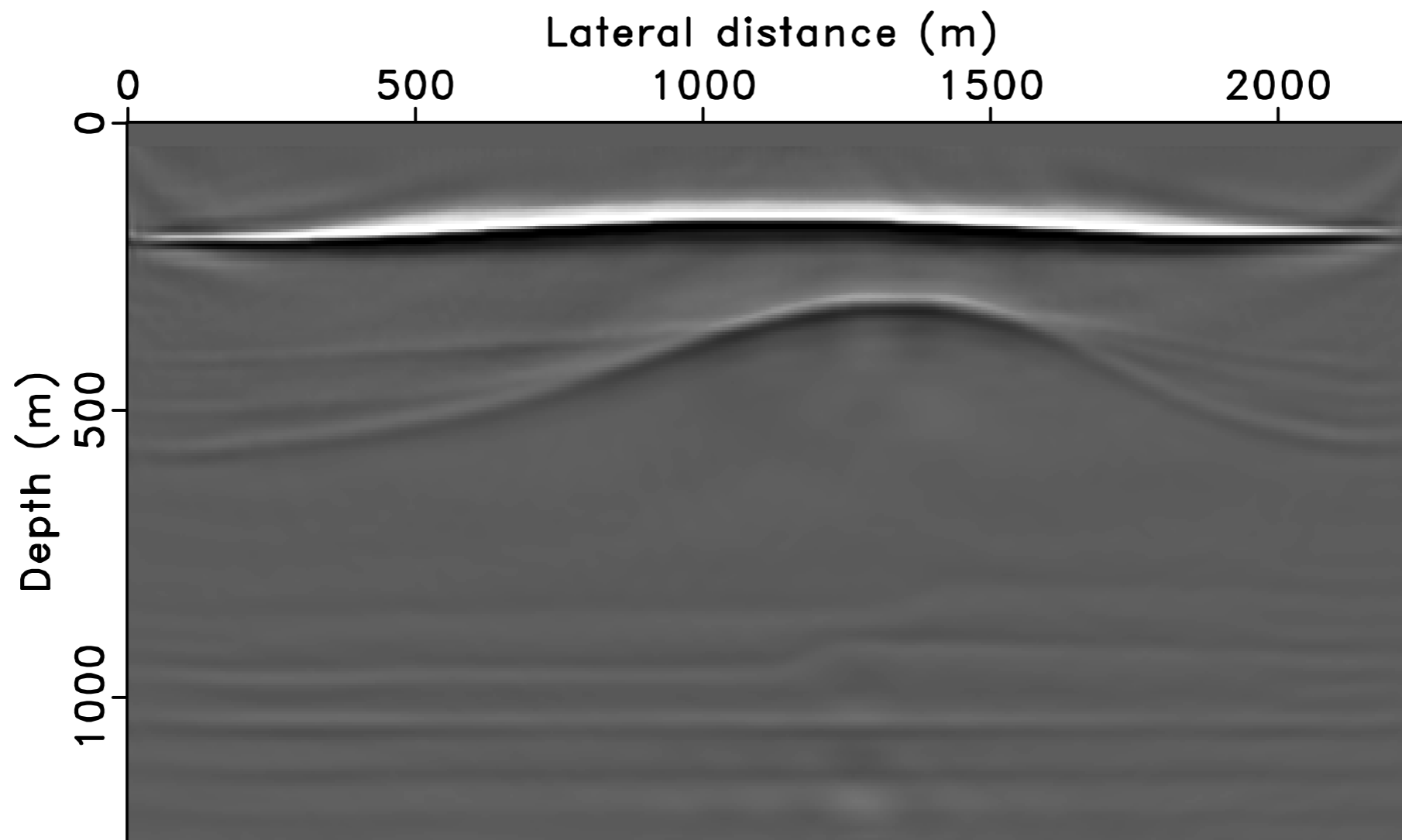
$$\hat{\mathbf{P}} \mathbf{W} \approx \widehat{\nabla \mathbf{F}}[\mathbf{m}, (\hat{\mathbf{Q}} - \hat{\mathbf{P}}) \mathbf{W}] \delta \mathbf{m}$$

Highly *efficient* formulation that

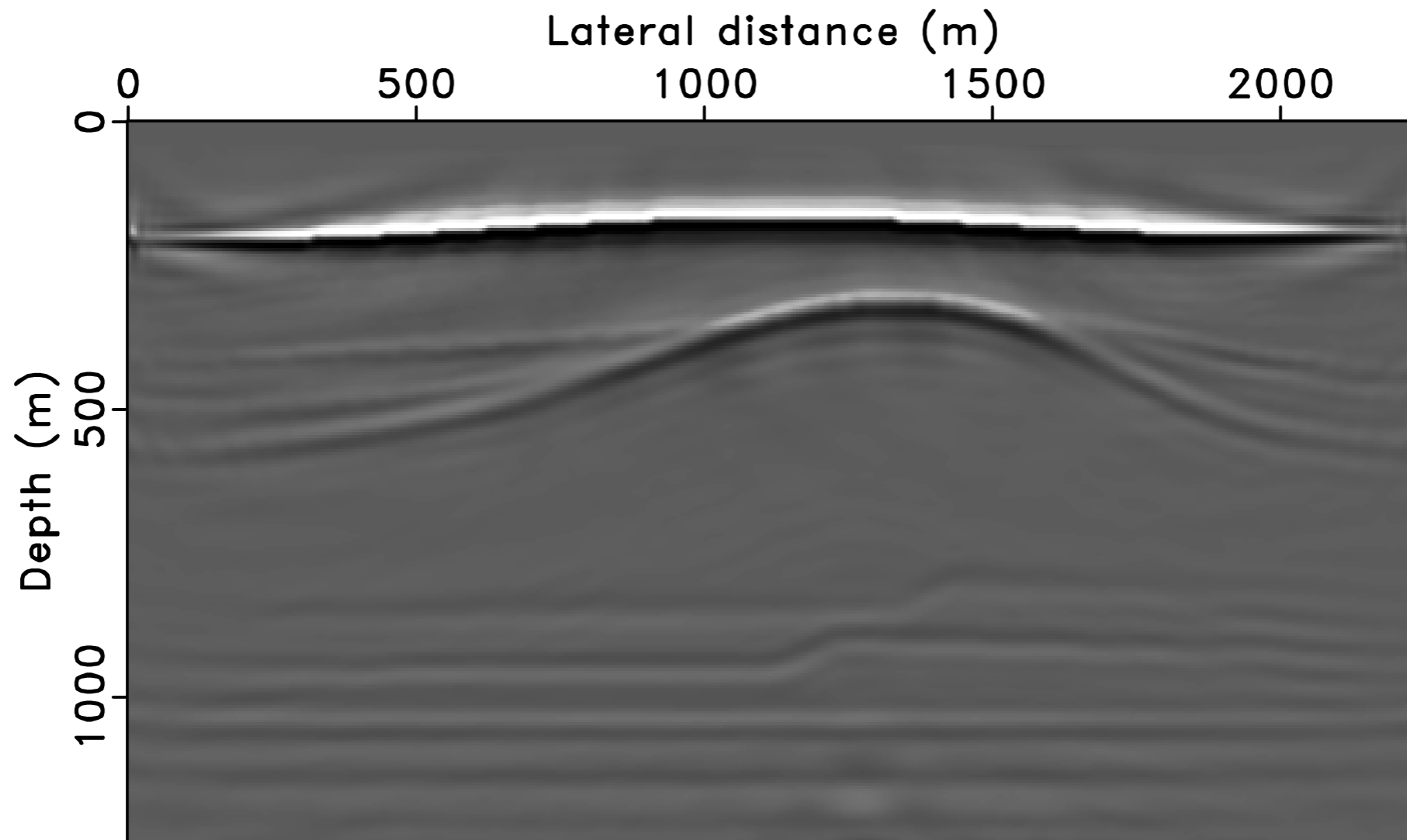
- ▶ *reduces #* of PDE solves
- ▶ *is conducive* to image-domain *sparsity-promotion*

Migration from marine '*simultaneous*' data

inversion from *EPSI inverted* Green's function

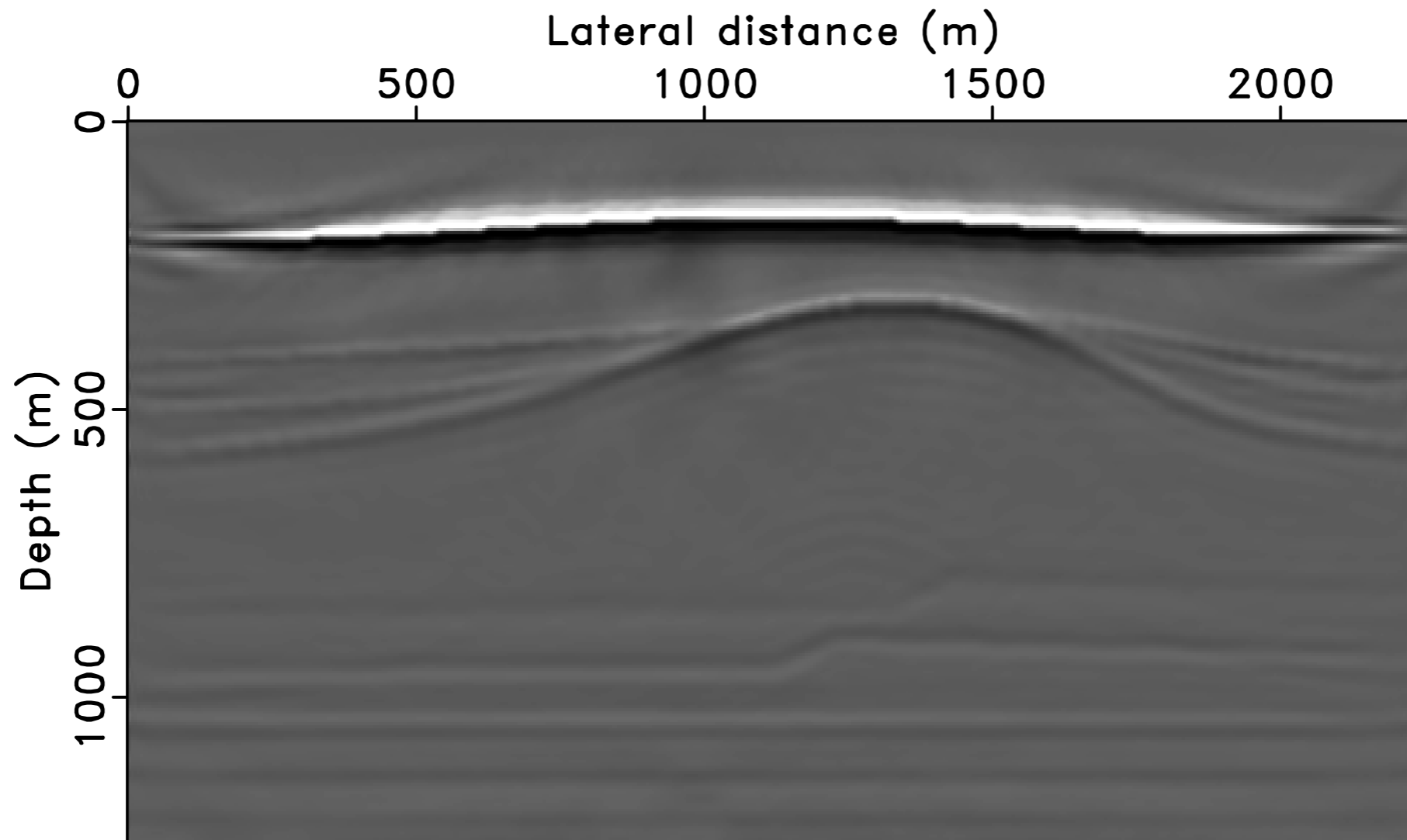


Migration from marine '*simultaneous*' data inversion from *total* data



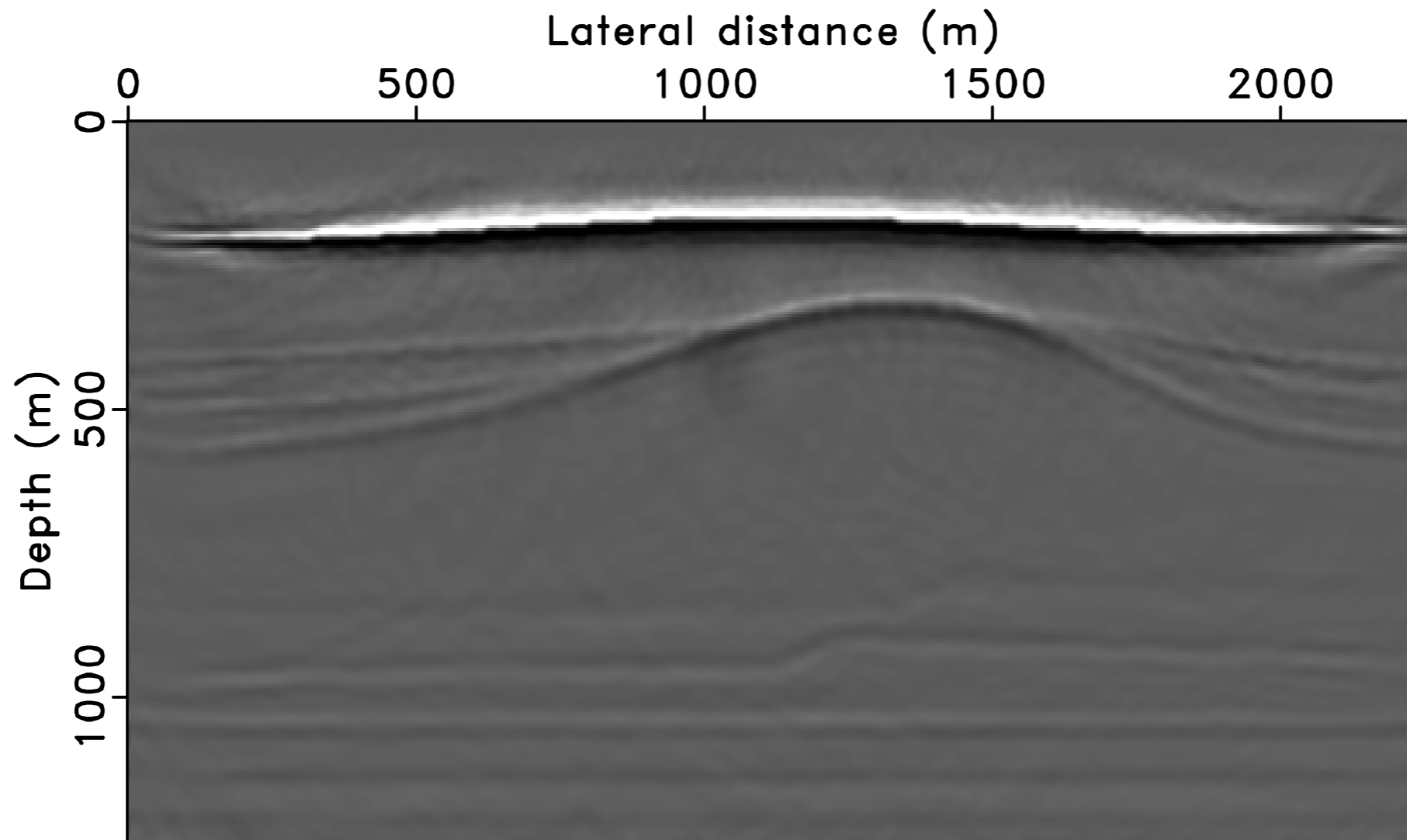
Migration from complete data with source-encoding

inversion from *total* data, 10 super-shots



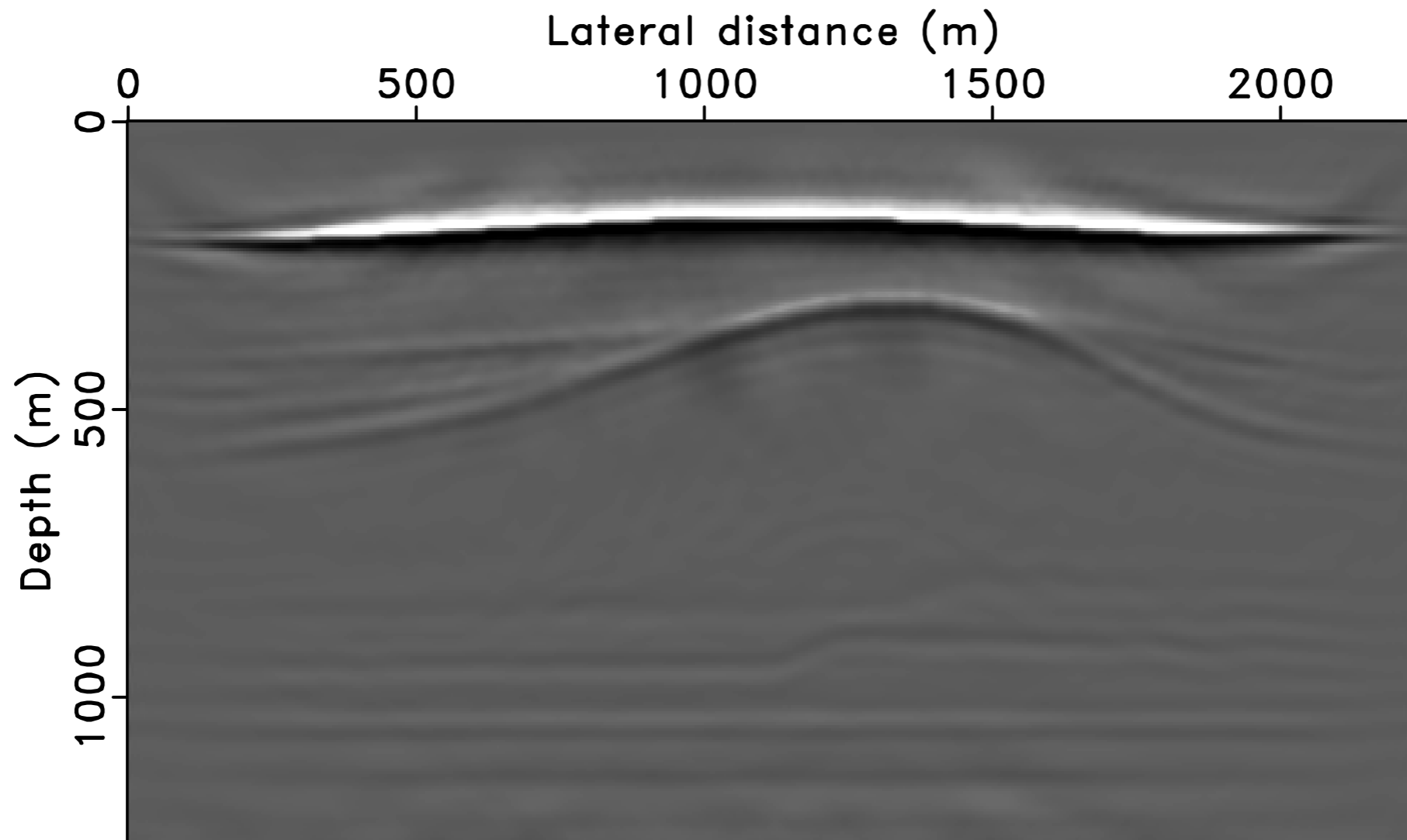
Migration from complete data with source-encoding

inversion from *total* data, 2 super-shots, no renewal



Migration from complete data with source-encoding

inversion from *total* data, 2 super-shots, renewal



Observations

Combination of *EPSI* or *interferometric* deconvolution with *imaging* via *areal* sources allows us to

- ▶ exploit *image-domain sparsity* & *information* from *multiples*
- ▶ do multi-D convolutions/correlations with wave solver

Costs and *reliance* on *full* sampling can be brought down by

- ▶ simultaneous sourcing, random time dithering, or a combination thereof
- ▶ but *adaptive* method *requires velocity* information

Approach III

With ‘black-box’ access to matvecs
(SRME multiple prediction including on-the-fly interpolation)

- ▶ use *randomized SVDs* allow us to do a low-rank approximation to factorize

$$\hat{\mathbf{P}} \approx \hat{\mathbf{L}}\hat{\mathbf{R}}^T$$

- ▶ reduces memory imprint and matvec costs
- ▶ allows us to conduct *velocity* analysis
- ▶ but requires ‘full’ data

Opportunity

Adapt *recent matrix-completion* techniques with *maxnorms*

Allows us to estimate low-rank approximations from incomplete directly data by solving

$$\underset{\mathbf{L}, \mathbf{R}}{\text{minimize}} \|\mathbf{b} - \mathcal{A}(\mathbf{LR}^*)\|_2^2 + \mu \|\mathbf{LR}^*\|_*$$

- ▶ *nuclear norm is approximated by maxnorm*
- ▶ *opens possibility to scale to 3D*
- ▶ *challenge is to find appropriate low-rank ‘domain’ (e.g., midpoint/offset)*

Observations

‘Multiples *facilitate recovery* from severe undersamplings.

Large data volumes impede data-space recovery and *require* exploration of other types of structure.

Image-domain wave simulators can carry the weight of ‘data-driven’ *approaches*

- ▶ and *really* shine with *simultaneous* sources & renewals
- ▶ but require velocity-model information

Q: relationship free surface BC & EPSI-like techniques?