THE UNIVERSITY OF BRITISH COLUMBIA | VANCOUVER

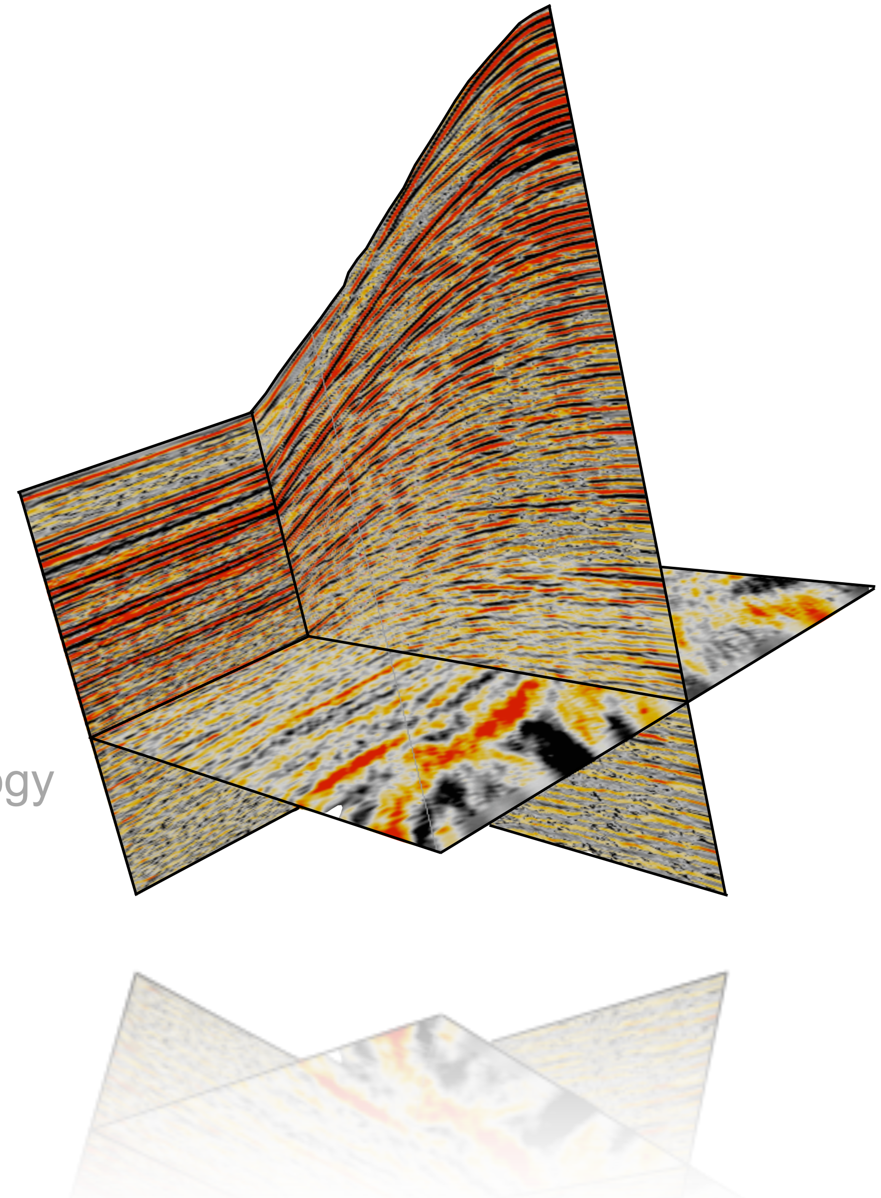
Seismic wavefield inversion with curvelet-domain sparsity promotion

Felix J. Herrmann*
fherrmann@eos.ubc.ca

Deli Wang**
wangdeli@email.jlu.edu.cn

***Seismic Laboratory for Imaging & Modeling**
Department of Earth & Ocean Sciences
The University of British Columbia

****Jilin University**
College of Geoexploration Science and Technology



SEG
Las Vegas, November 9-14

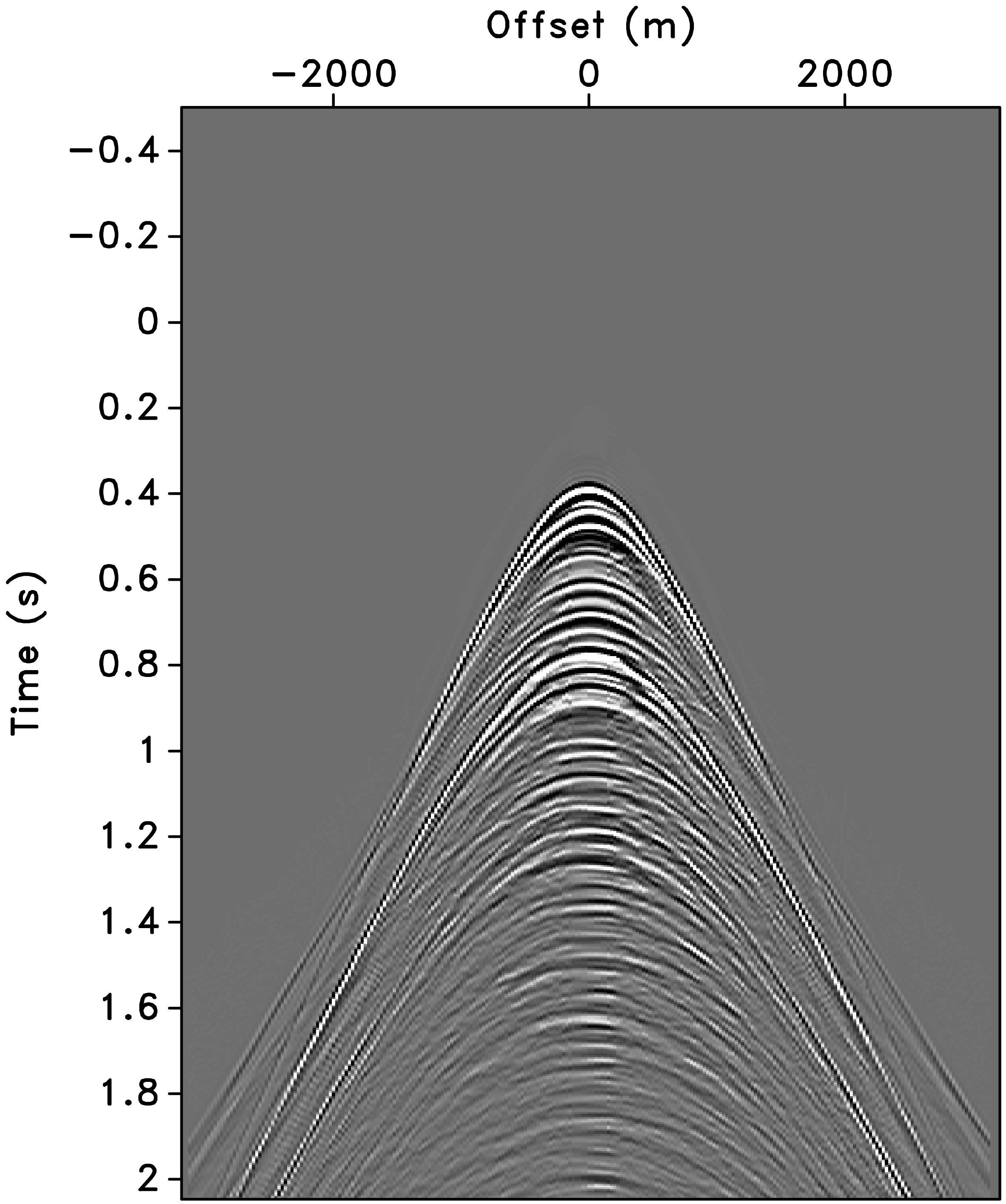
General statement

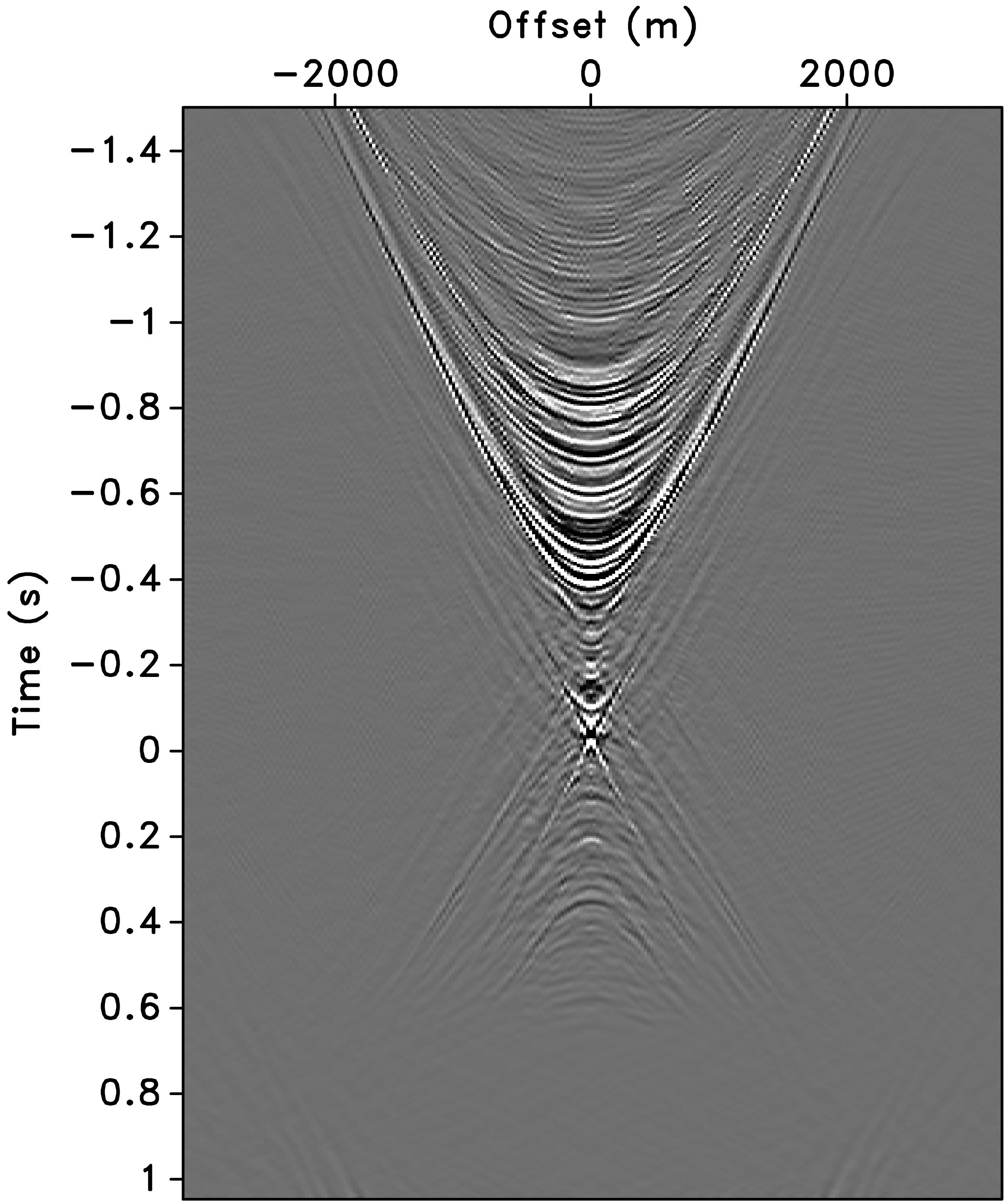
- Recent resurgence of wavefield inversions
  - *imaging* where the ‘sunken’ source & data-residue wavefields are inverted [Claerbout, Berkout and others]
  - *focal transform* where primaries are deconvolved to focus data [Berkhout ‘06]
  - *interferometric deconvolution* where wavefields are inverted [Vasconcelos & Snieder ’08, Wapenaar ‘08]
  - *data inverse* where the data itself is inverted [Berkhout ‘06]

- Challenge is to ***stably*** invert these *wavefields*
  - in the presence of noise, finite aperture, and source signatures
  - for incomplete & simultaneously acquired data

- Propose a *regularization* based on curvelet-domain sparsity promotion enforced by nonlinear optimization ...

Inverse data-matrix





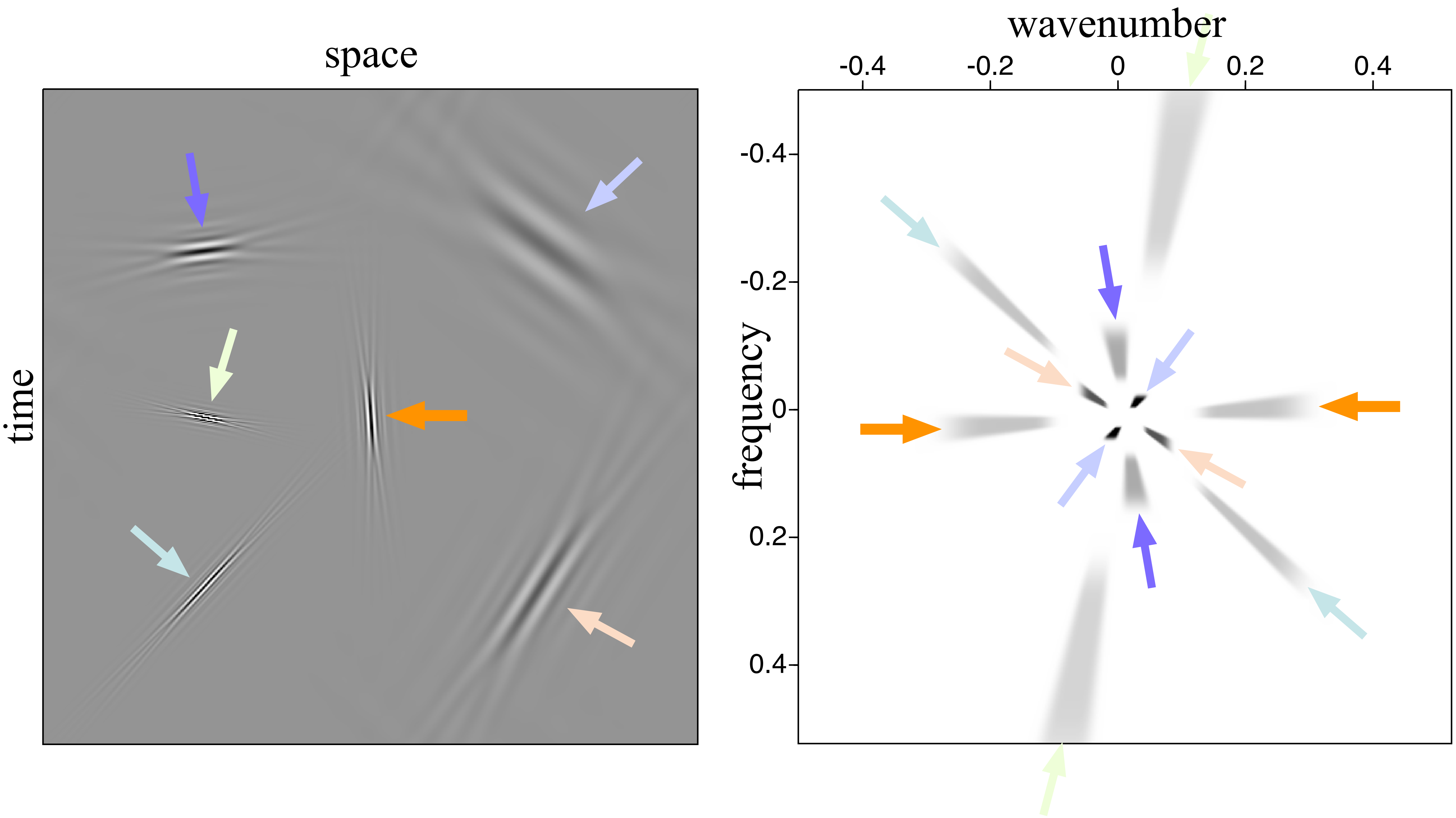
Problem statement

- Seismic wavefield inversions = multi-D deconvolutions
- Corresponds to the inversion of Berkhout's [‘82] data matrix
  - monochromatic
  - inverted by damped & weighted least-squares matrix inversion [Wapenaar ‘08]
- Suffers from instabilities that limit applicability to real data
  - noise
  - finite acquisition
  - incomplete data
- **Present a framework for stable inversion with sparsity promotion.**

Motivation

- Successful application of curvelets
  - wavefield recovery from missing traces [F.J.H & Hennenfent ’08, Hennenfent & F.J.H ‘08]
  - wavefield recovery from compressive simultaneous simulations [F.J.H et. al ‘08]
  - curvelet-transform [Candes et. al. ‘06] based sparsity promotion
- Robustness & uplift of *focused* curvelet-based wavefield recovery
  - curvelet-regularized inversion of the primary-data-matrix operator [F.J.H et. al. ‘07-’08]
  - incorporation of *a priori* information
  - improved wavefield recovery from missing traces
- Insights from compressive sampling [Donoho ’06, Candes et.al ’06, Lin & F.J. H ‘07]
  - jittered sampling [Hennefent & F.J.H]
  - blended-source design [F.J.H et.al ‘08]
  - one-norm solvers [Hennefent et. al. ‘08]
- Move from multi-D *correlations* to multi-D *deconvolutions* ....

2D discrete curvelets

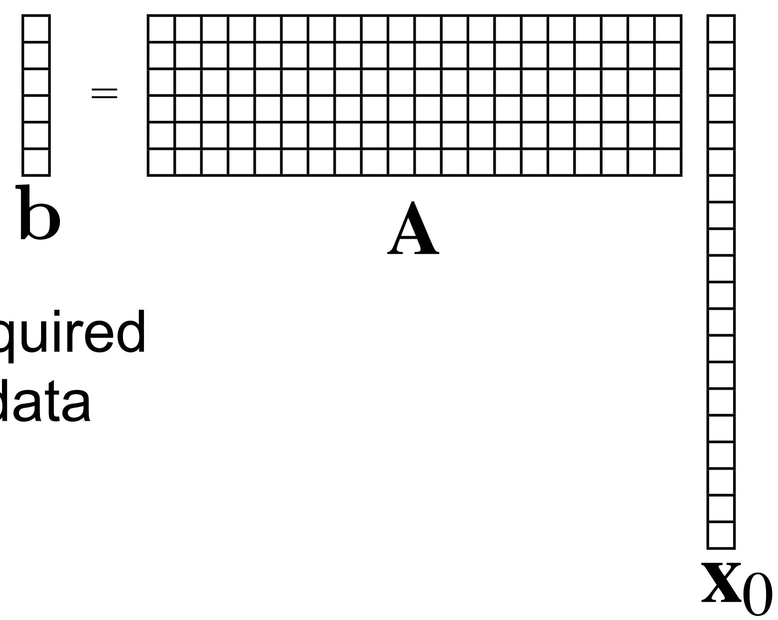


Sparsity-promoting program

Solve for $\mathbf{x}_0$

complete wavefield (transform domain)

restriction operator



acquired data

with $\mathbf{A} := \mathbf{R}\mathbf{S}^H$

redundant sparsifying transform

with

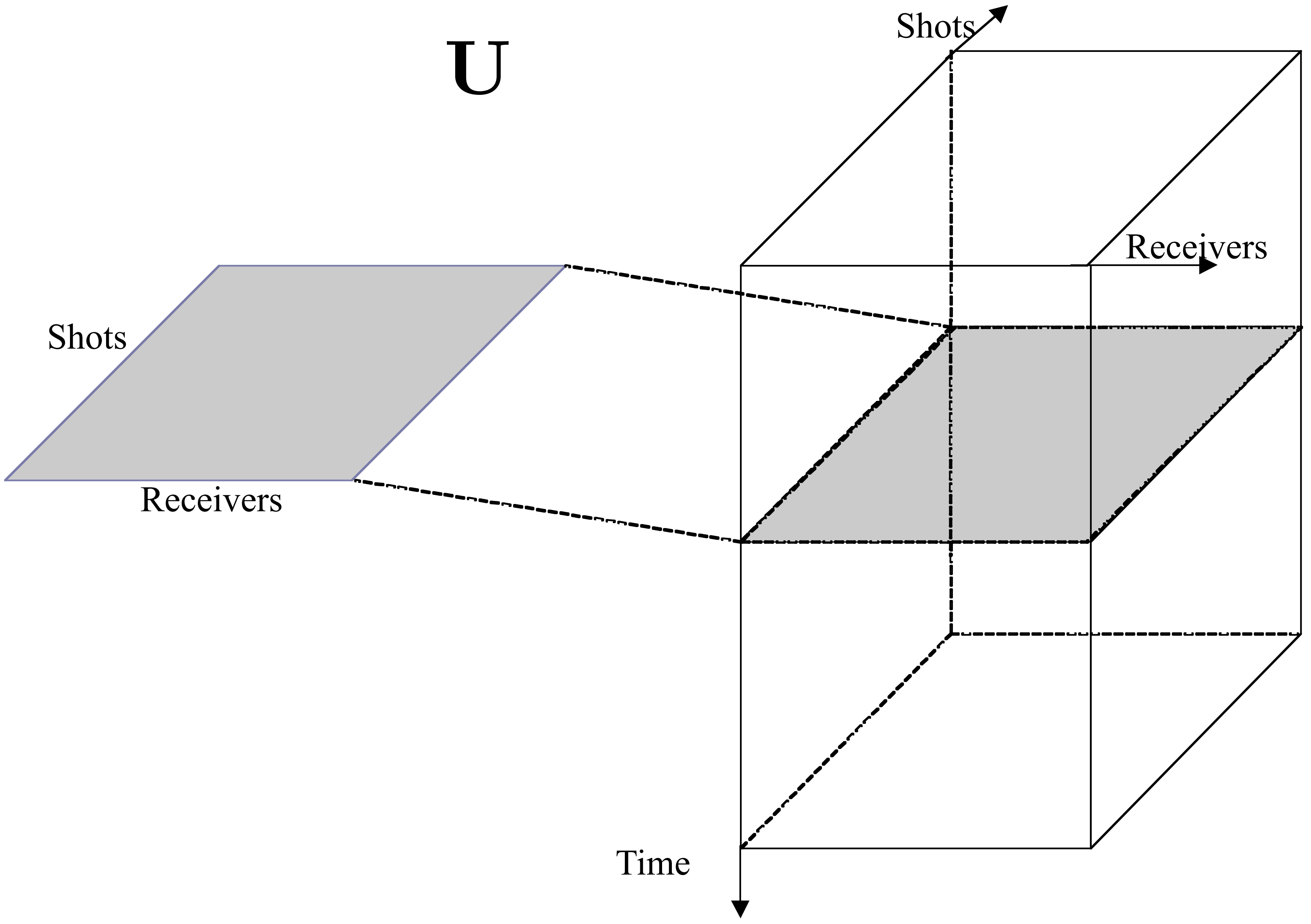
$$\mathbf{P}_\epsilon : \begin{cases} \tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2 \leq \epsilon \\ \tilde{\mathbf{g}} = \mathbf{S}^H \tilde{\mathbf{x}} \end{cases}$$

Observations:

- exploits ***sparsity*** in the curvelet domain as a ***prior***
- finds the sparsest set of curvelet coefficients that match (incomplete) data
- inverts an *underdetermined* system

[Sacchi et al.'98]
[Xu et al.'05]
[Zwartjes and Sacchi'07]
[F.J.H and Hennenfent'08]

Data matrix (2D seismic line)



Subsampling by restriction (picking)

For each *time-slice* along *source-receiver* coordinates

$$\mathbf{B} = \overbrace{\mathbf{R}^{\Sigma_r}}^{\text{remove rows}} \mathbf{U} \overbrace{\left(\mathbf{R}^{\Sigma_s}\right)^*}^{\text{remove cols}}$$

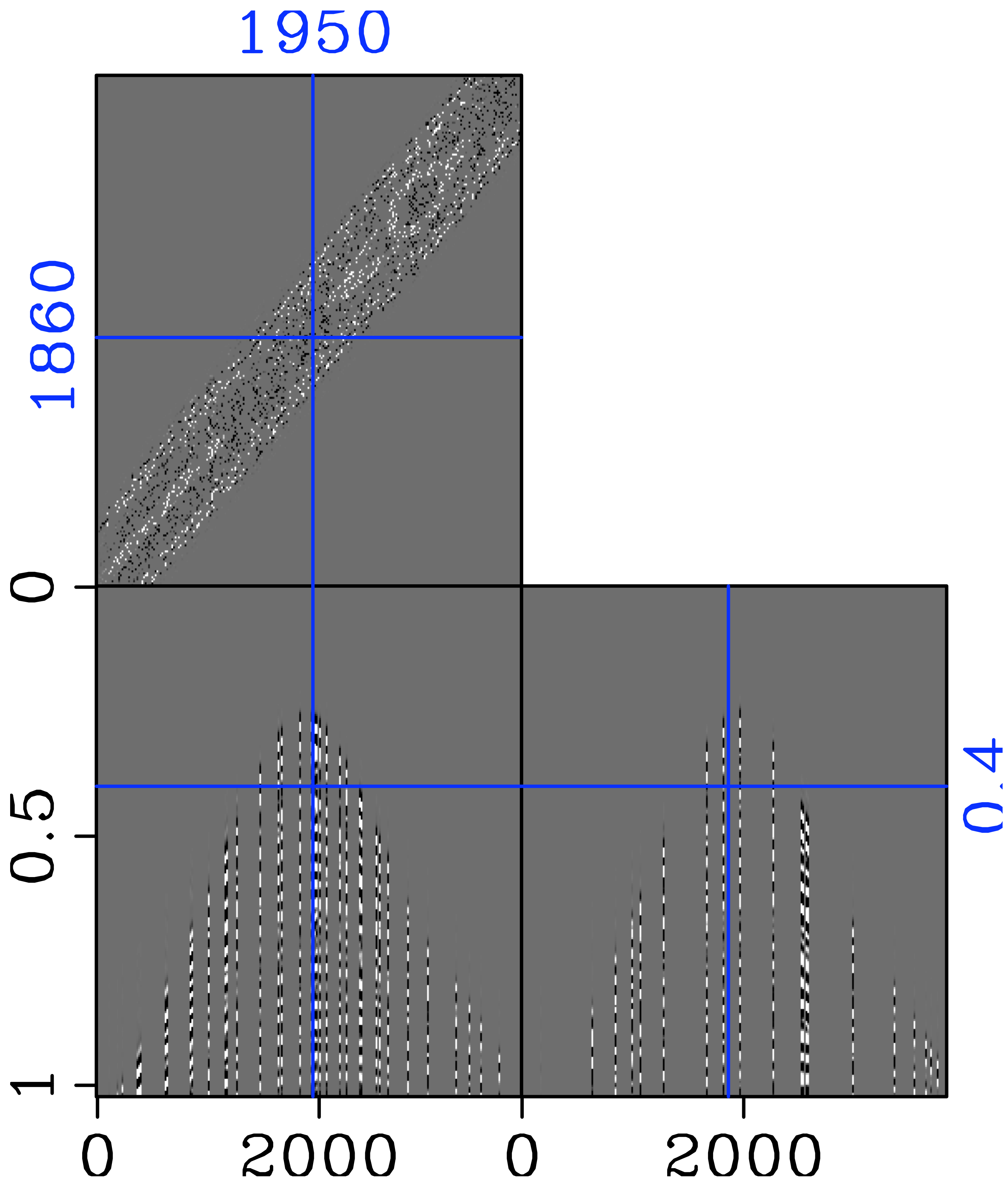
or more succinctly with Kronecker products

$$\mathbf{b} = \left(\mathbf{R}^{\Sigma_s} \otimes \mathbf{R}^{\Sigma_r}\right) \mathrm{vec}\left(\mathbf{U}\right)$$

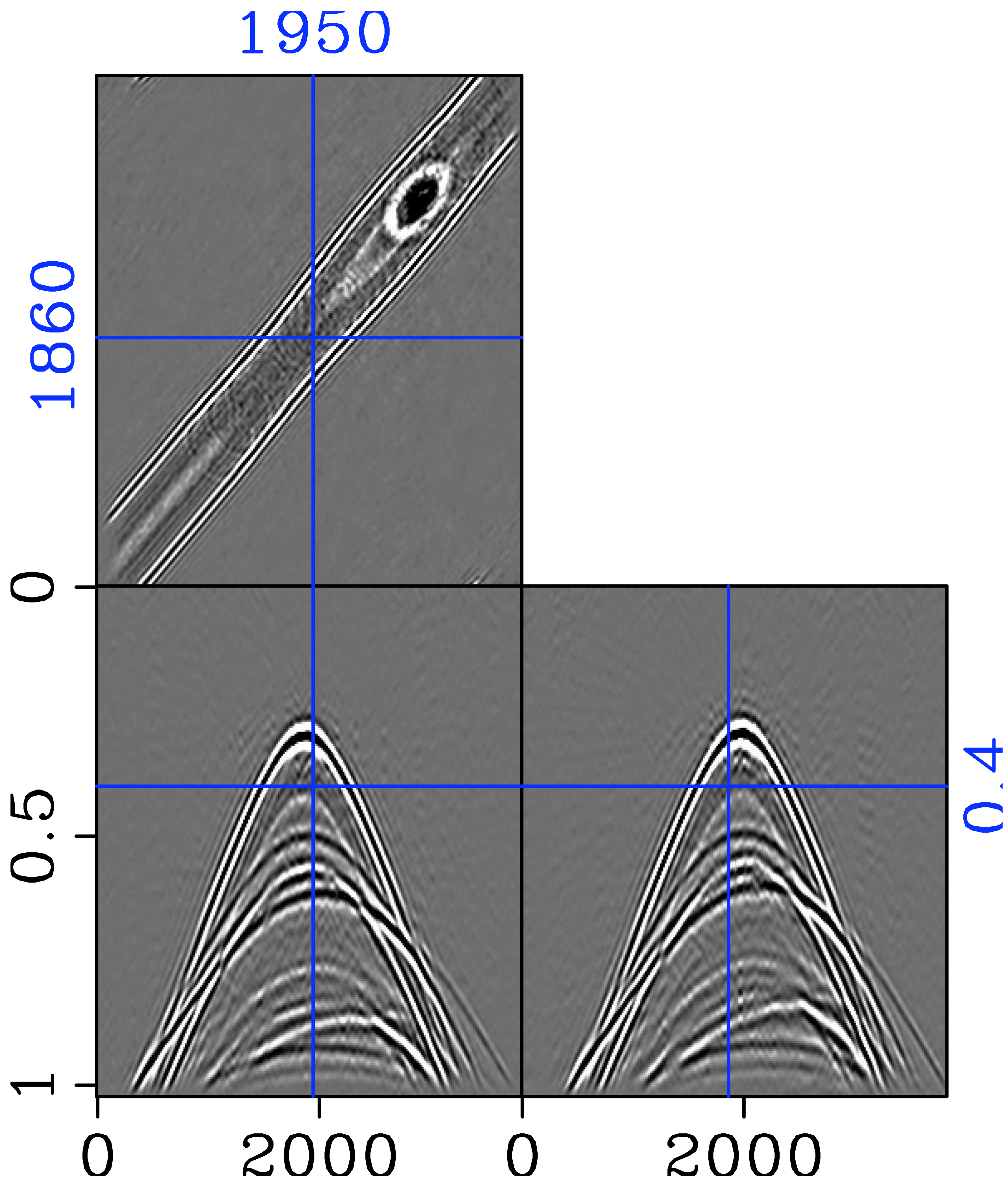
For all time slices in the data matrix, we have

$$\mathbf{R} = \left(\mathbf{R}^{\Sigma_s} \otimes \mathbf{R}^{\Sigma_r} \otimes \mathbf{I}\right)$$

Incomplete data



Curvelet-domain sparsity promotion



Wavefield recovery by sparsity promotion

$$\begin{cases} \mathbf{R} &= \left(\mathbf{R}^{\Sigma_s} \otimes \mathbf{R}^{\Sigma_r} \otimes \mathbf{I}\right) & \text{(source-receiver restriction)} \\ \mathbf{b} &= \mathbf{R}\text{vec}\,(\mathbf{U}) & \text{(incomplete data)} \\ \mathbf{A} &= \mathbf{R}\mathbf{S}^H & \\ \tilde{\mathbf{x}} &= \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} & \|\mathbf{A}\mathbf{x} - \mathbf{b}\|_2 \leq \epsilon \\ \tilde{\mathbf{U}} &= \text{vec}^{-1}\left(\mathbf{S}^T \tilde{\mathbf{x}}\right) & \text{(recovered data)} \end{cases}$$

Curvelet sparsity underlies success of wavefield recovery

- from large percentages of traces missing [F.J.H & Hennenfent ‘08]
- improvements from jittered subsampling [Hennenfent & F.J.H ‘08]

Formulation

- only exploits curvelet-domain sparsity
- misses focusing with wavefields

Can we extend this formalism to invert wavefields ....?

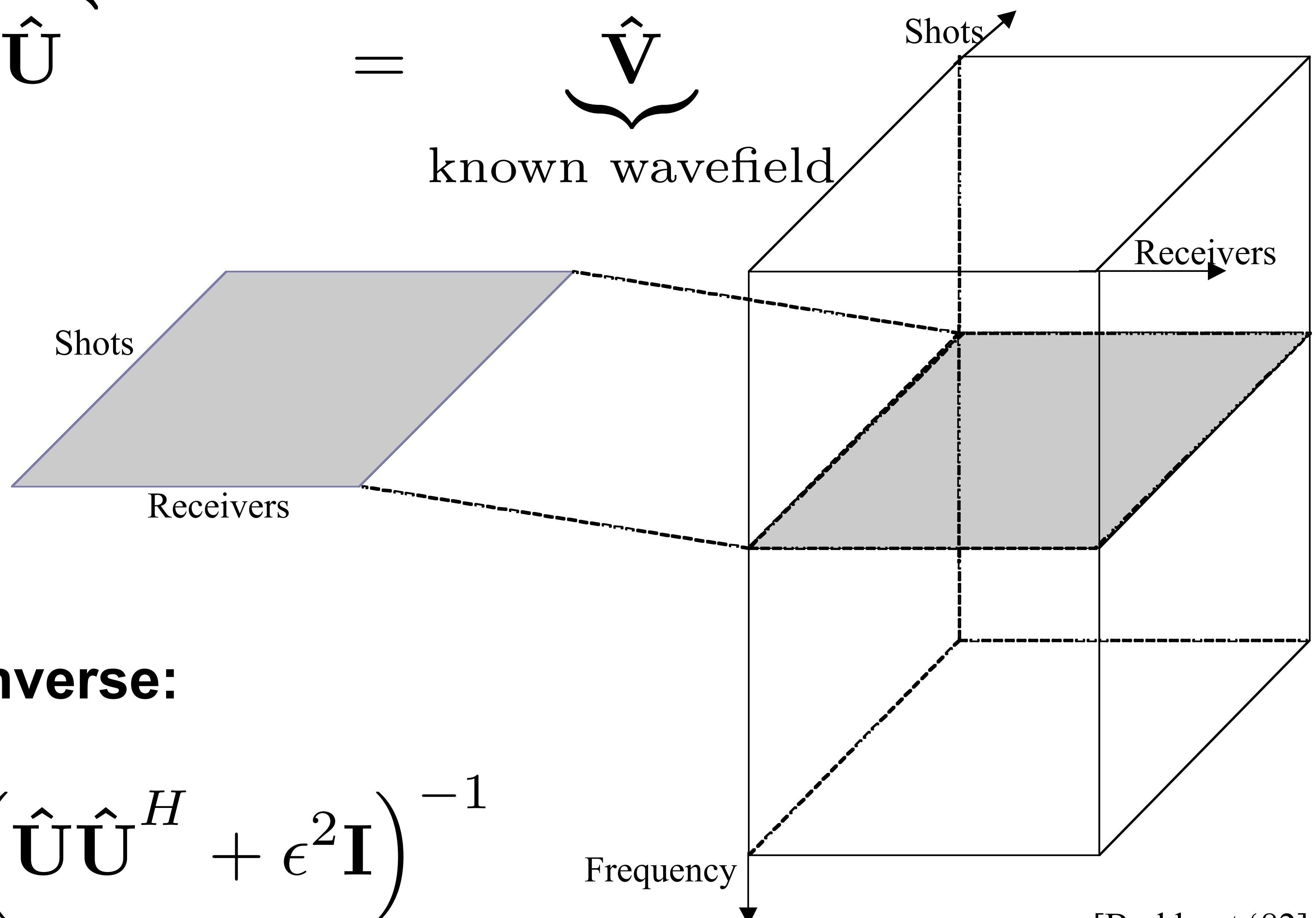
Common-problem formulation

- Extension of curvelet-based wavefield recovery to include (de)focusing with data-matrices defined by wavefields [F.J.H et.al ’07-’08]
  - define *linear* data-matrix operators
  - multi-D *convolutions*
  - and their adjoint multi-D *correlations*
- Incorporates *prior* information
- Use transform-domain sparsity to stably invert for all frequencies
- Combination of sparsity and focusing

Common approach: damped least-squares

Monochromatic **forward model:**

$$\underbrace{\hat{\mathbf{G}}}_{\text{unknown ''image''}} \overbrace{\hat{\mathbf{U}}}^{\text{to be inverted wavefield}} = \underbrace{\hat{\mathbf{V}}}_{\text{known wavefield}}$$



Monochromatic **pseudo-inverse:**

$$\hat{\mathbf{G}} = \hat{\mathbf{V}}\hat{\mathbf{U}}^{H}\left(\hat{\mathbf{U}}\hat{\mathbf{U}}^{H} + \epsilon^{2}\mathbf{I}\right)^{-1}$$

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

Curvelet-based wavefield inversion (CWI)

Cast into rigorous *linear-algebra* framework, i.e.

$$\hat{\mathbf{G}}_i \hat{\mathbf{U}}_i = \hat{\mathbf{V}}_i,\ i = 1 \cdots n_f$$

which with the Kronecker identity

$$\mathrm{vec}\left(\mathbf{AXB}\right) = \left(\mathbf{B}^H \otimes \mathbf{A}\right) \mathrm{vec}\left(\mathbf{X}\right)$$

becomes for each *frequency*

$$\left(\mathbf{I} \otimes \hat{\mathbf{U}}_\mathbf{i}\right) \mathrm{vec}\left(\hat{\mathbf{G}}_\mathbf{i}\right) = \mathrm{vec}\left(\hat{\mathbf{V}}_i\right),\ i = 1 \cdots n_f$$

Set up a system for ***all*** *frequencies* and incorporate the *temporal* ***Fourier*** transform ....

Curvelet-based wavefield inversion (CWI)

$$\overbrace{\left(\mathbf{F}^H \begin{bmatrix} \mathbf{I} & \otimes & \hat{\mathbf{U}}_1 \\ & \vdots & \\ \mathbf{I} & \otimes & \hat{\mathbf{U}}_{n_f} \end{bmatrix} \mathbf{F}\right)}^{\mathbf{U}} \overbrace{\mathrm{vec}\left(\begin{bmatrix} \mathbf{G}_1 \\ \vdots \\ \mathbf{G}_{n_f} \end{bmatrix}\right)}^{\mathbf{g}} = \overbrace{\mathrm{vec}\left(\begin{bmatrix} \mathbf{V}_1 \\ \vdots \\ \mathbf{V}_{n_f} \end{bmatrix}\right)}^{\mathbf{v}}$$

with $\mathbf{F} = (\mathbf{I} \otimes \mathbf{I} \otimes \mathcal{F})$ (*temporal* Fourier transform)

Linear system is

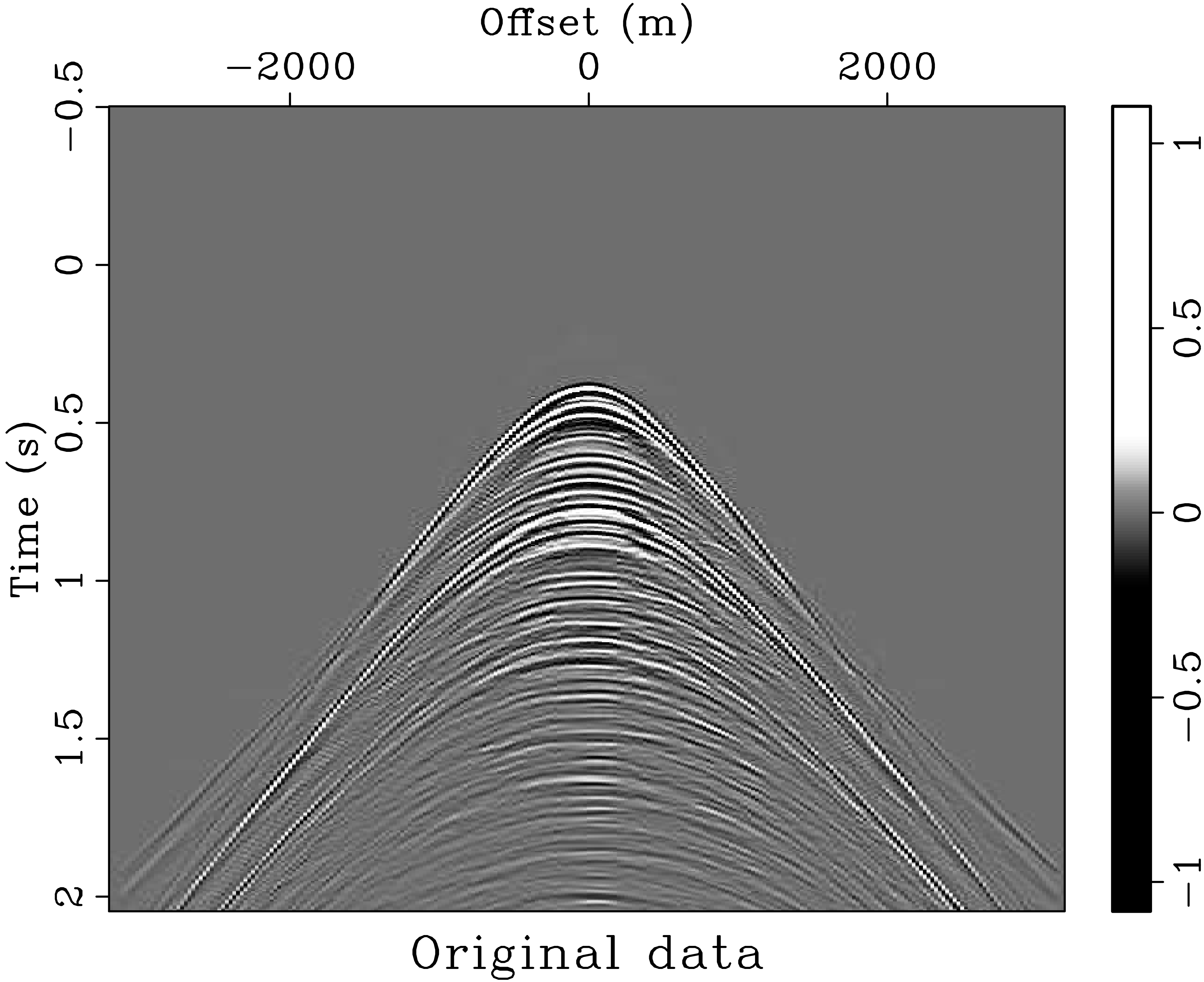
- conducive to curvelet-based wavefield *inversion* with *sparsity* promotion
- versatile
- conducive to compressive subsampling (e.g. missing trace or blended acquisition)

Focal transform [Berkhout ’06, F.J.H et.al ‘07-’08]

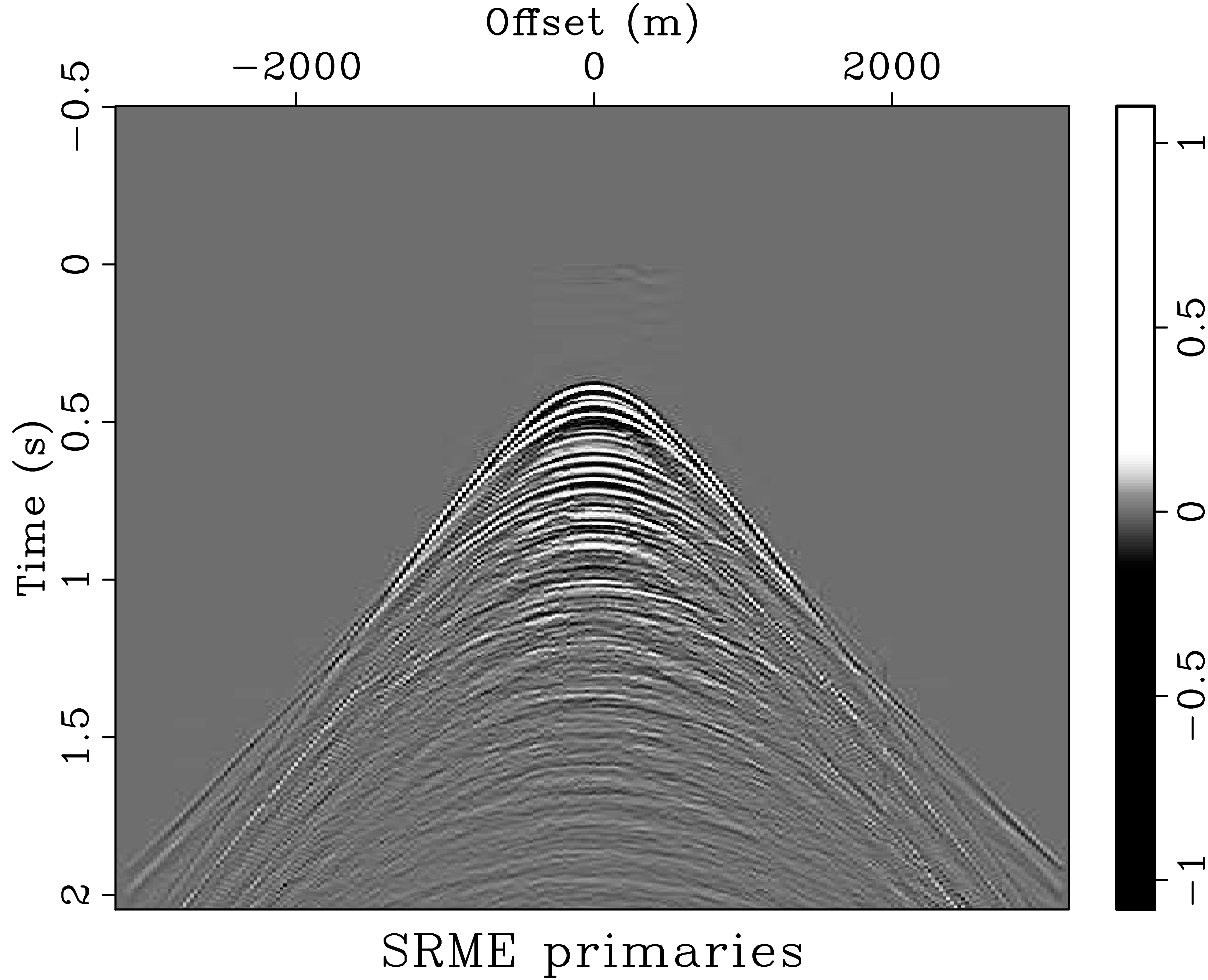
$$
\begin{cases}
\mathbf{U} & = \boldsymbol{\Delta}\mathbf{P} \qquad \text{(primary data-matrix operator)} \\
\mathbf{V} & = \mathbf{P} \qquad \text{(total data matrix)} \\
\mathbf{b} & = \text{vec}\,(\mathbf{V}) \\
\mathbf{A} & = \mathbf{U}\mathbf{C}_3^H \qquad \text{(focused 3-D curvelet transform)} \\
\tilde{\mathbf{x}} & = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \|\mathbf{A}\mathbf{x} - \mathbf{b}\|_2 \le \epsilon \\
\tilde{\mathbf{G}} & = \text{vec}^{-1}\left(\mathbf{C}_3^H \tilde{\mathbf{x}}\right) \qquad \text{(focused data)}
\end{cases}
$$

- *primary data-matrix* operator is *inverted*
- total data multi-D *deconvolved* with the *primaries*
- primaries *focused* to a *directional* source
- *first-order multiples* mapped to *primaries*

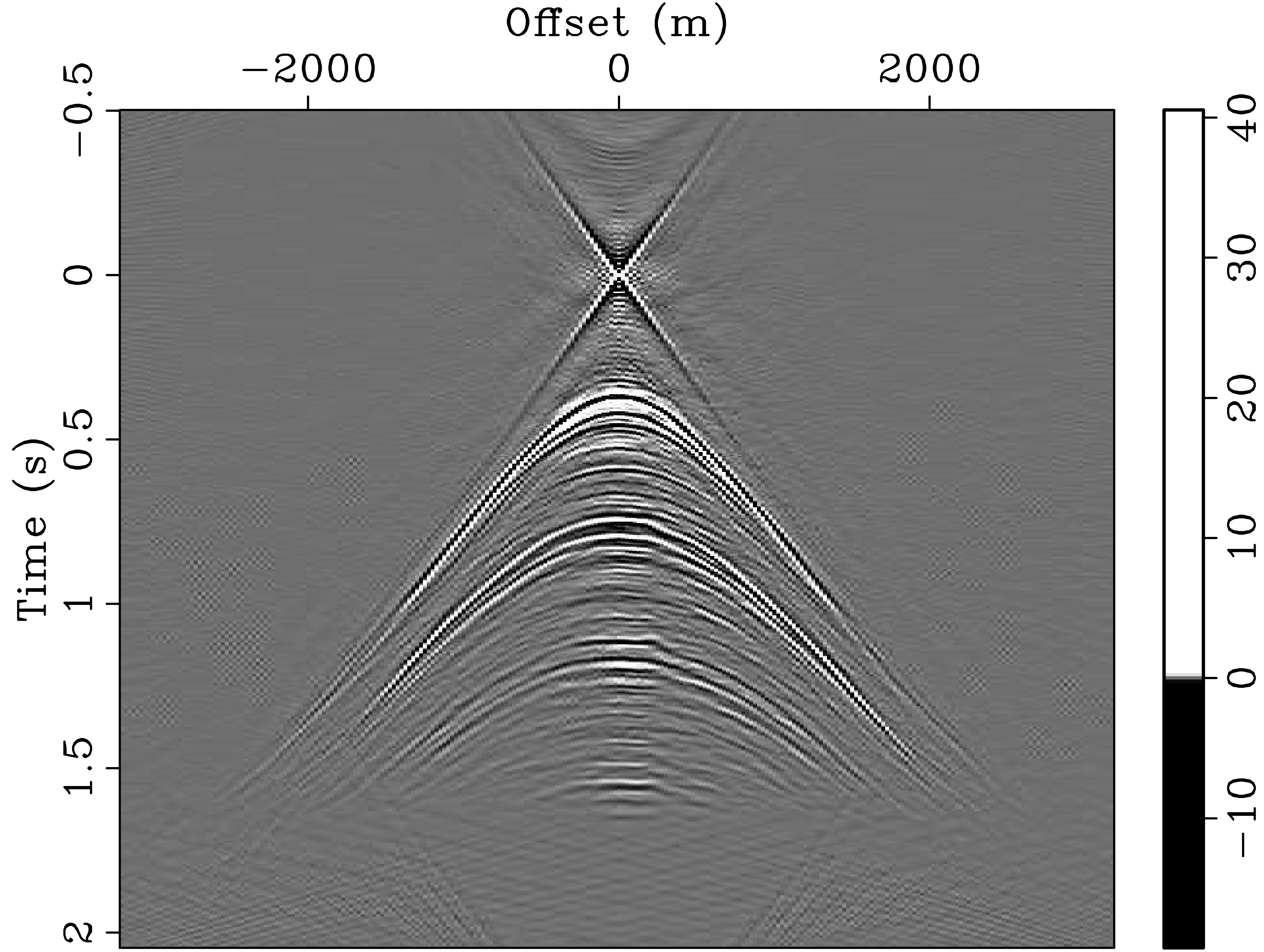
Slice from the total data matrix (V)



Slice from primary data-matrix operator (U)



Focused/multi-D deconvolved data (G)



Curvelet-based wavefield inversion (CWI)

$$\mathbf{P}_\epsilon : \begin{cases} \mathbf{b} &= \text{vec}\left(\mathbf{V}\right) \\ \mathbf{A} &= \mathbf{U}\mathbf{S}^H \\ \tilde{\mathbf{x}} &= \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \|\mathbf{A}\mathbf{x} - \mathbf{b}\|_2 \le \epsilon \\ \tilde{\mathbf{G}} &= \text{vec}^{-1}\left(\mathbf{S}^T\tilde{\mathbf{x}}\right) \approx \underbrace{\mathbf{U}^\dagger}_{\text{"inverse"}} \quad \mathbf{V} \end{cases}$$

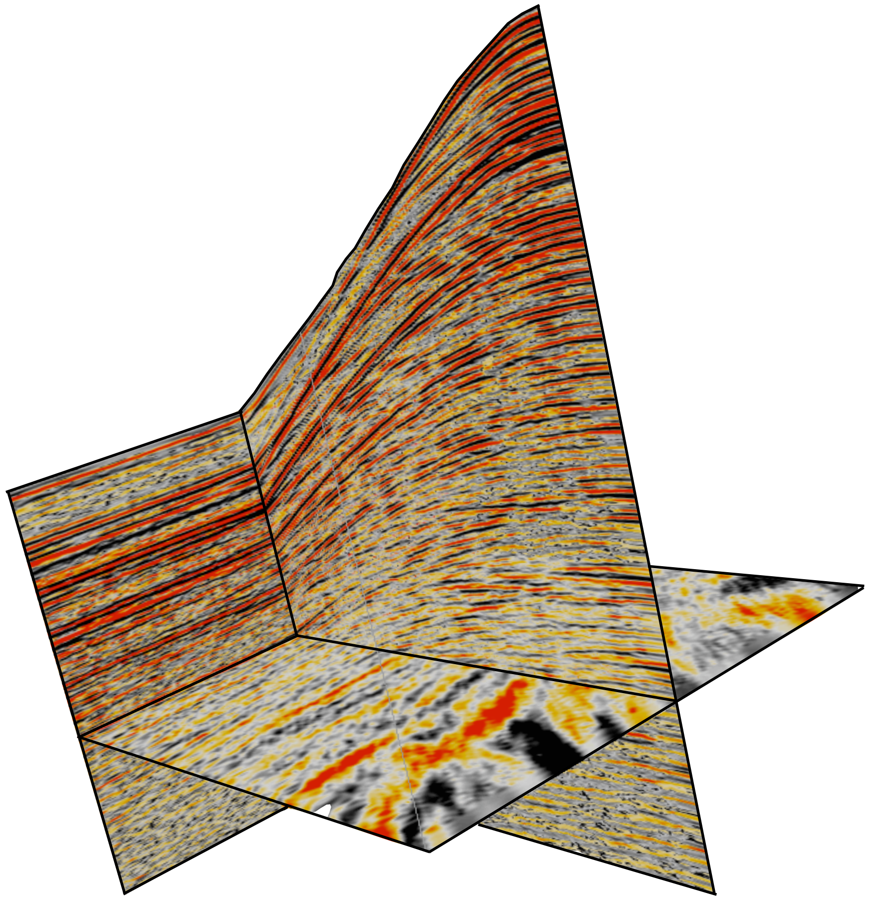
Corresponds to

- curvelet-sparsity *regularized* inversion
- multi-D *deconvolution* of the wavefield in the data matrix **U** with respect to the wavefield in the data matrix **V**

Applications

- *focused* wavefield recovery
- *defocussed* multiple prediction
- data *inverse*
- imaging of *blended* data

Focused wavefield recovery



SEG
Las Vegas, November 9-14

Motivation

- Exploit *wavefield* focusing in the solution of the *recovery* problem
  - invert subsampled primary data-matrix operator [F.J.H et.al ‘07-’08]
  - interpolate by taking the inverse focal and curvelet transforms

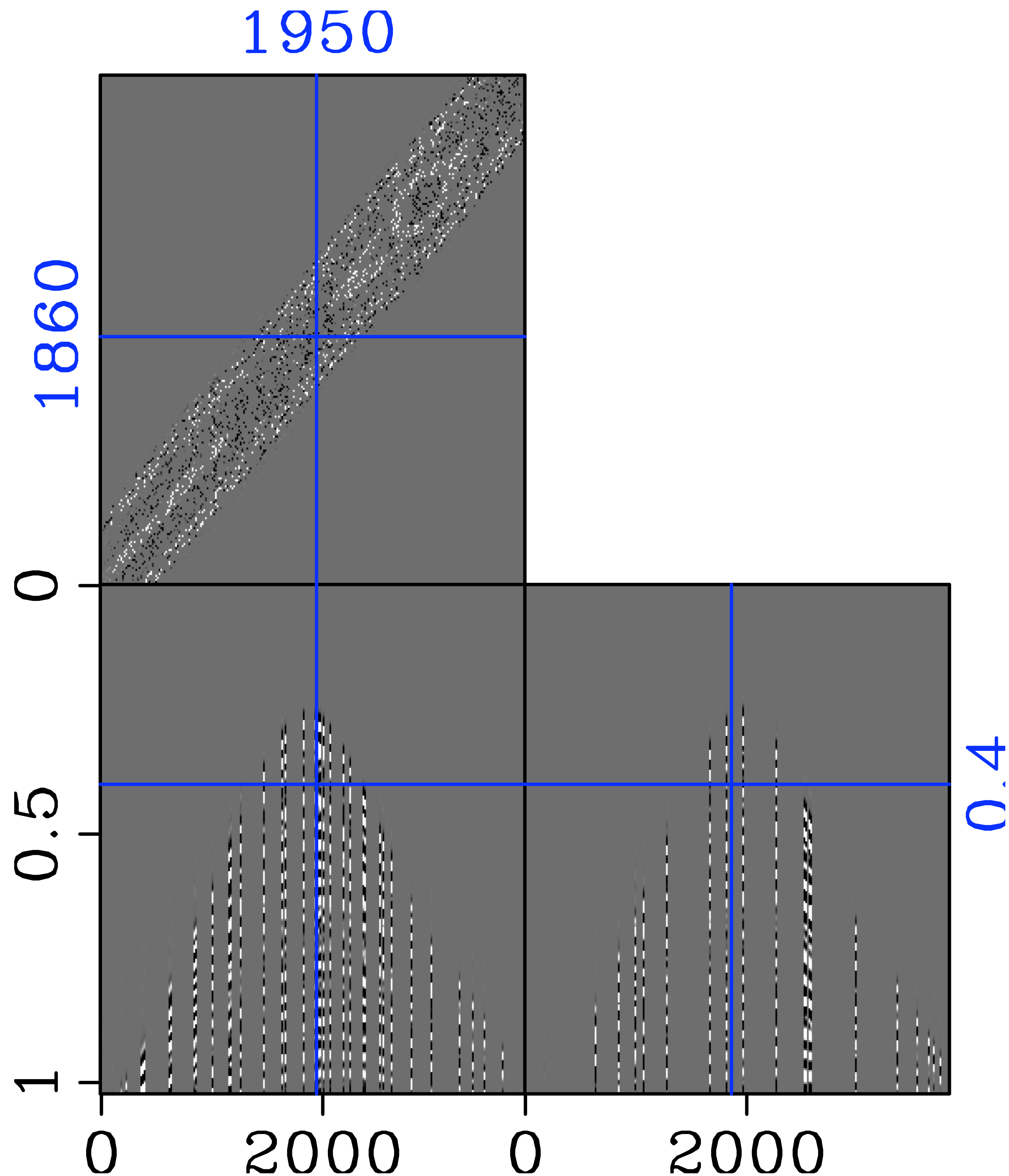
- Combination of sparsity and *wavefield* focusing
  - improved focusing => more sparsity
  - curvelet sparsity => better focusing

Focused wavefield recovery

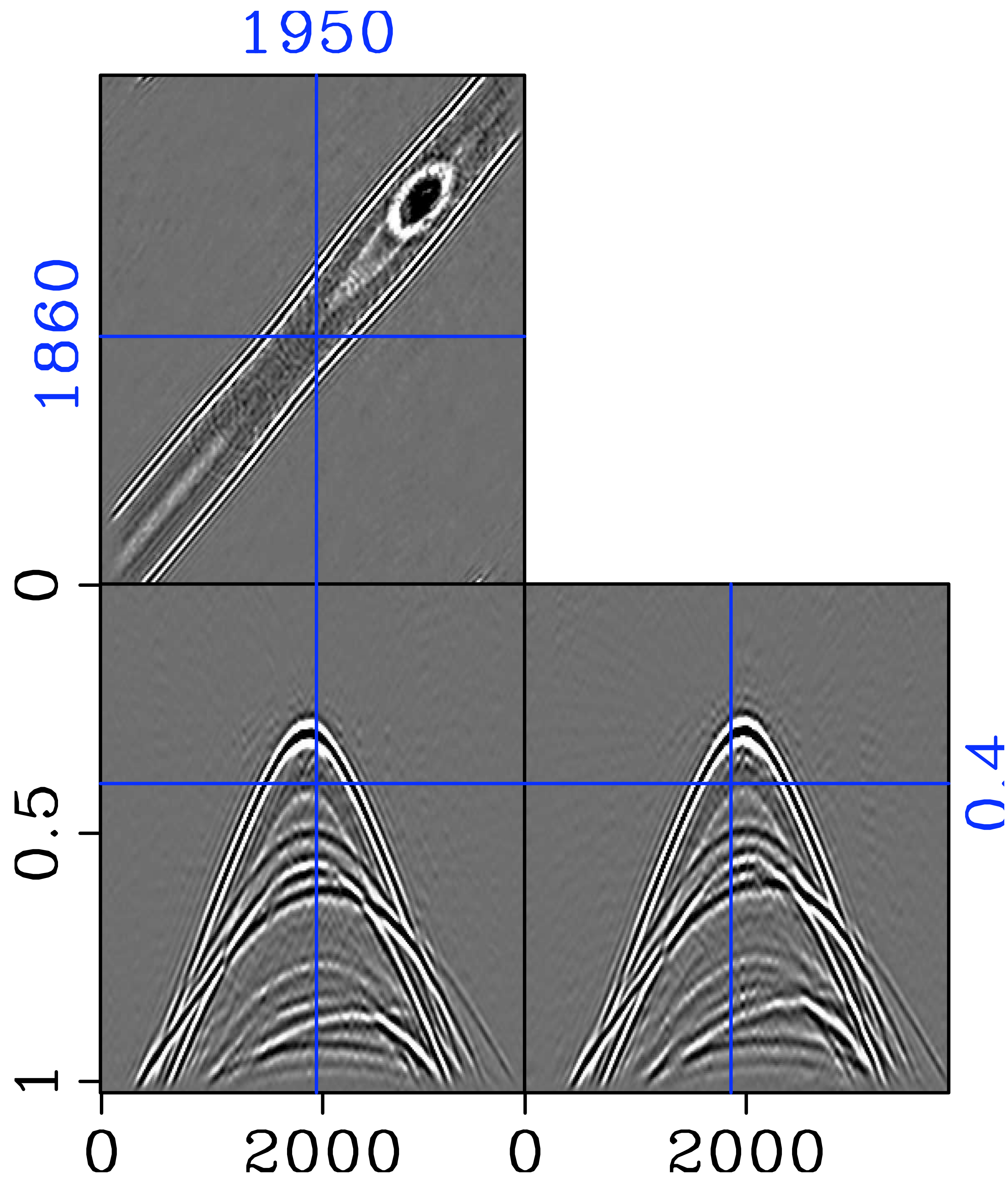
$$
\begin{cases}
\mathbf{R} & = \left(\mathbf{R}^{\Sigma_s} \otimes \mathbf{R}^{\Sigma_r} \otimes \mathbf{I}\right) \quad \text{(source-receiver restriction)} \\
\mathbf{V} & = \mathbf{P} \quad \text{(total data matrix)} \\
\mathbf{b} & = \mathbf{R}\mathrm{vec}\left(\mathbf{V}\right) \quad \text{(incomplete data)} \\
\mathbf{U} & = \mathbf{\Delta P} \quad \text{(primary data-matrix operator)} \\
\mathbf{A} & = \mathbf{R}\mathbf{S}^H \\
\mathbf{S}^H & = \mathbf{U}\mathbf{C}_3^H \quad \text{(focussed 3-D curvelet transform)} \\
\tilde{\mathbf{x}} & = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \|\mathbf{A}\mathbf{x} - \mathbf{b}\|_2 \leq \epsilon \\
\tilde{\mathbf{V}} & = \mathrm{vec}^{-1}\left(\mathbf{S}^H \tilde{\mathbf{x}}\right) \quad \text{(recovered data)}
\end{cases}
$$

- *Restrictions* along the *source-receiver* coordinates
- *Focusing* by *inversion* of the restricted *primary-data matrix* operator
- Reconstruction by *inverse* curvelet transform and *defocusing*

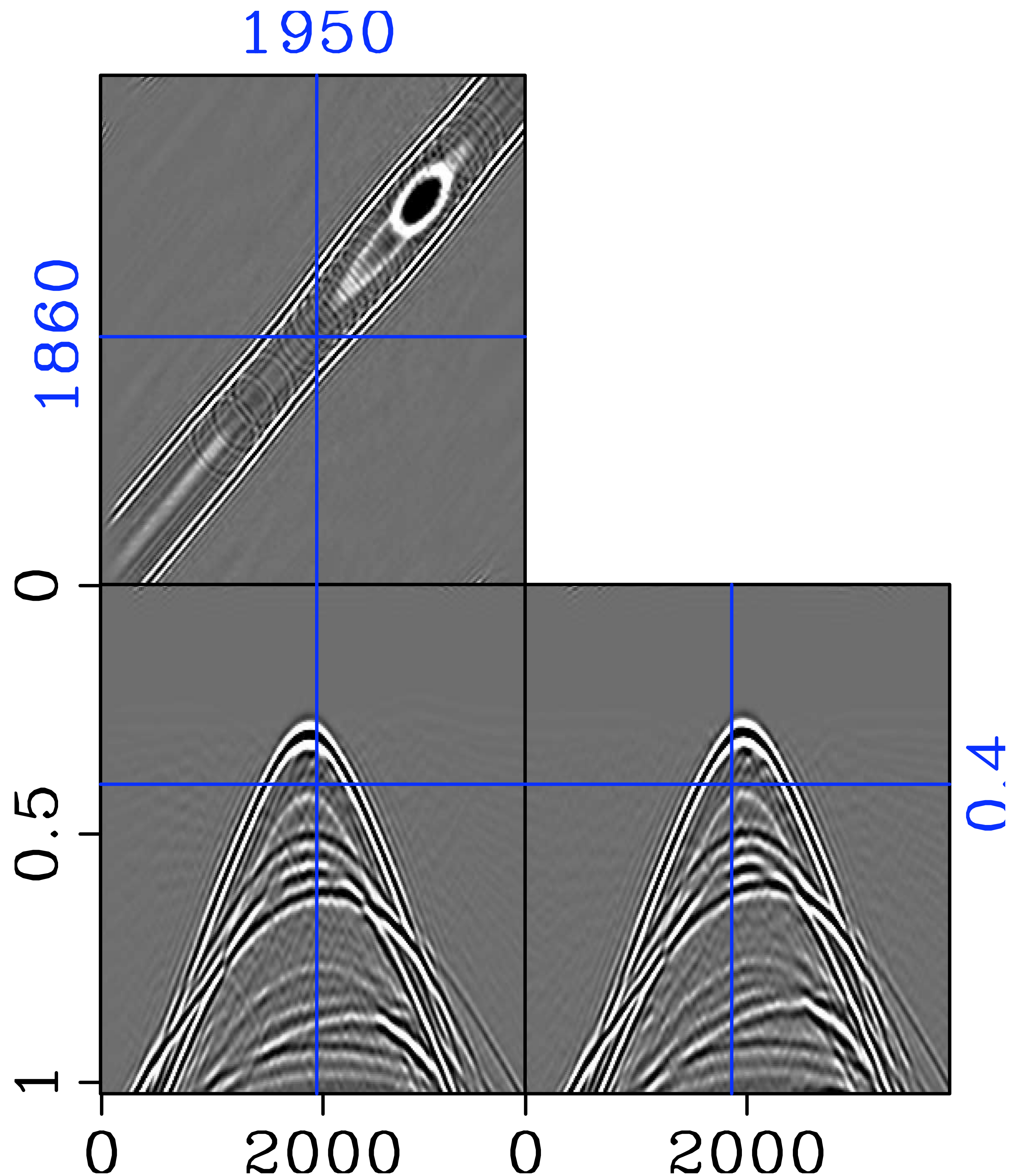
Incomplete data



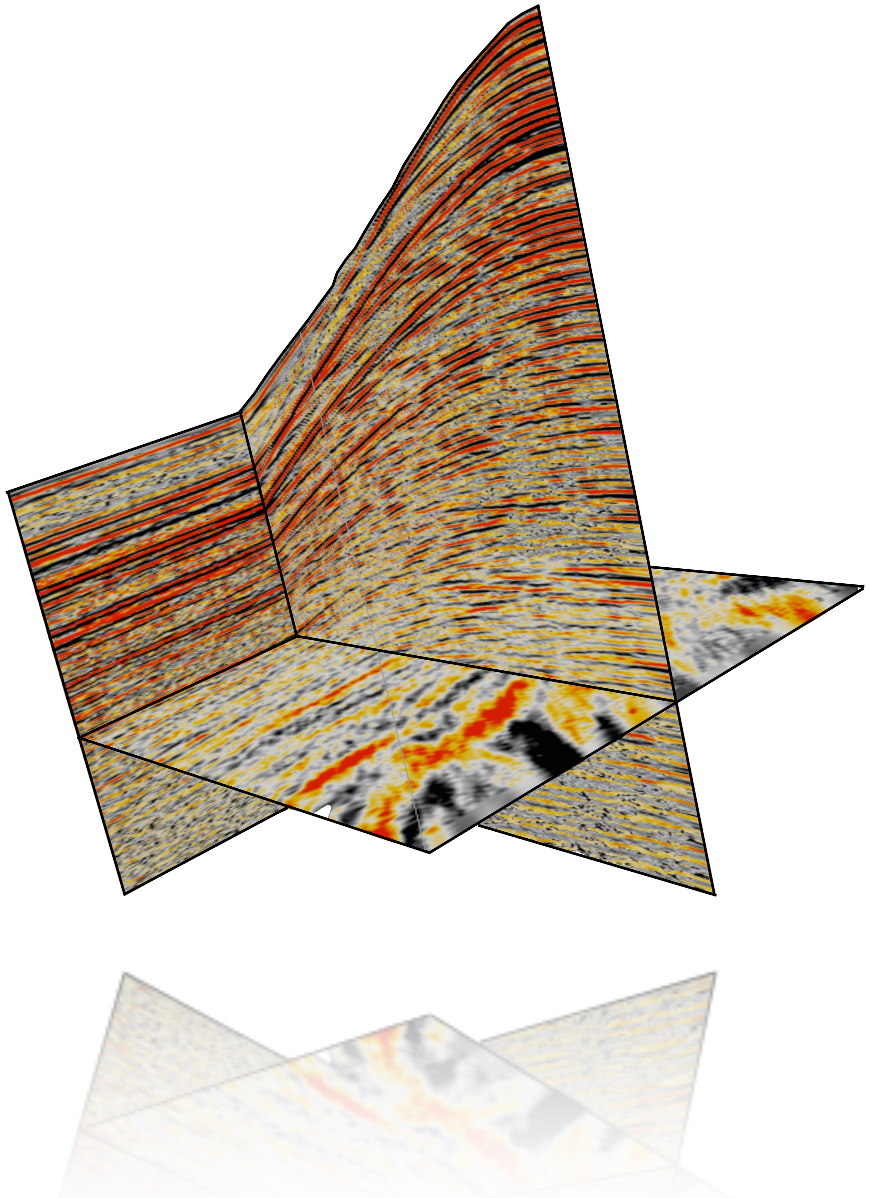
Curvelet-domain sparsity promotion



Focused curvelet-domain sparsity promotion



Defocussed multiple prediction



SEG
Las Vegas, November 9-14

Motivation

- *Multiple* prediction by multi-D *convolution* with the *primary data-matrix operator*
  - requires extensive *matching* to compensate for
    - the "source signature"
    - finite acquisition aperture
    - etc.

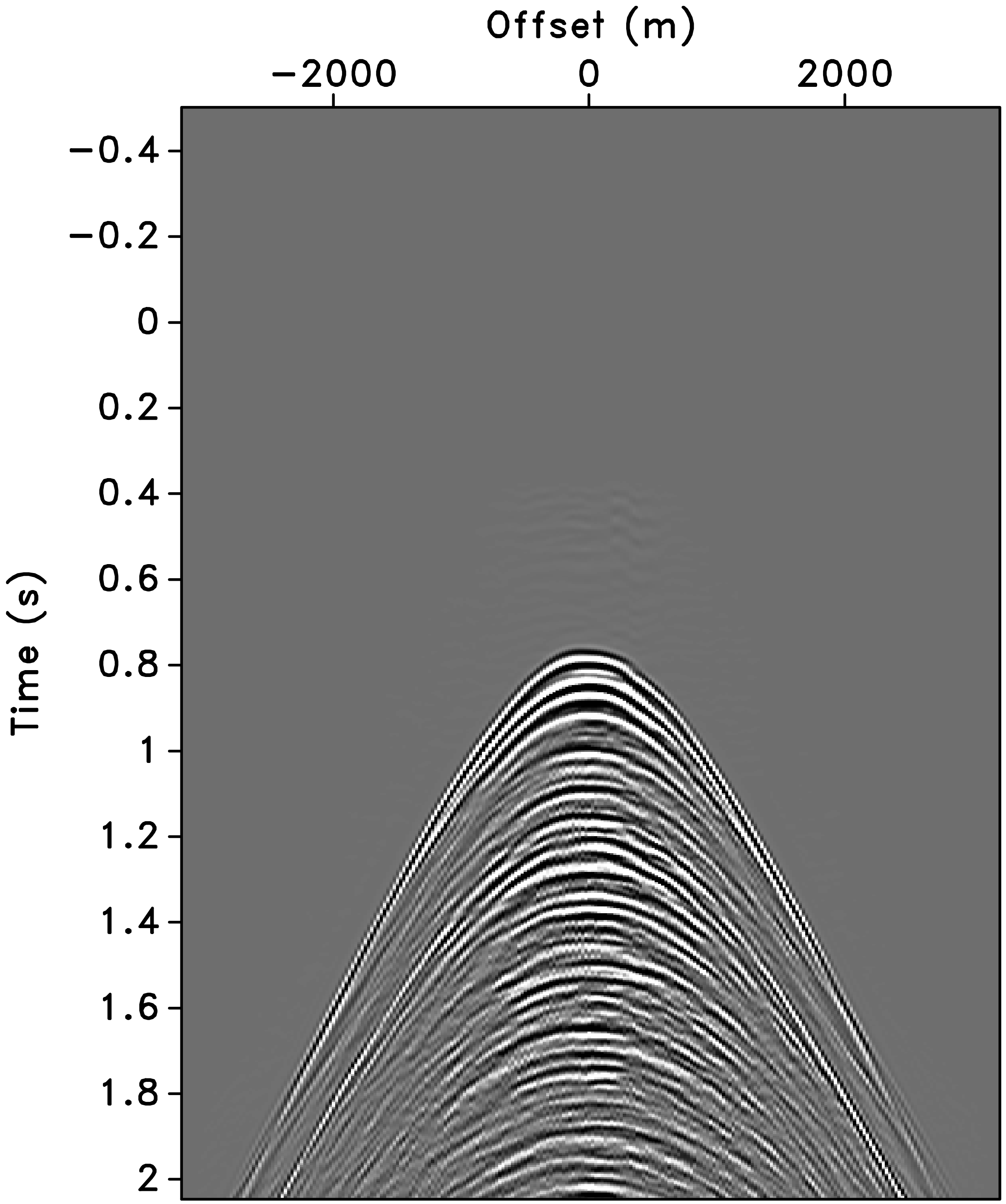
- *Defocussed* multiple prediction by multi-D *deconvolution* with the *primary data-matrix operator*
  - *inversion* of the *adjoint=multi-D correlation* with the *primary data-matrix operator*
  - compensates for the *amplitudes, finite aperture,* & *source wavelet*

Defocussed multiple prediction

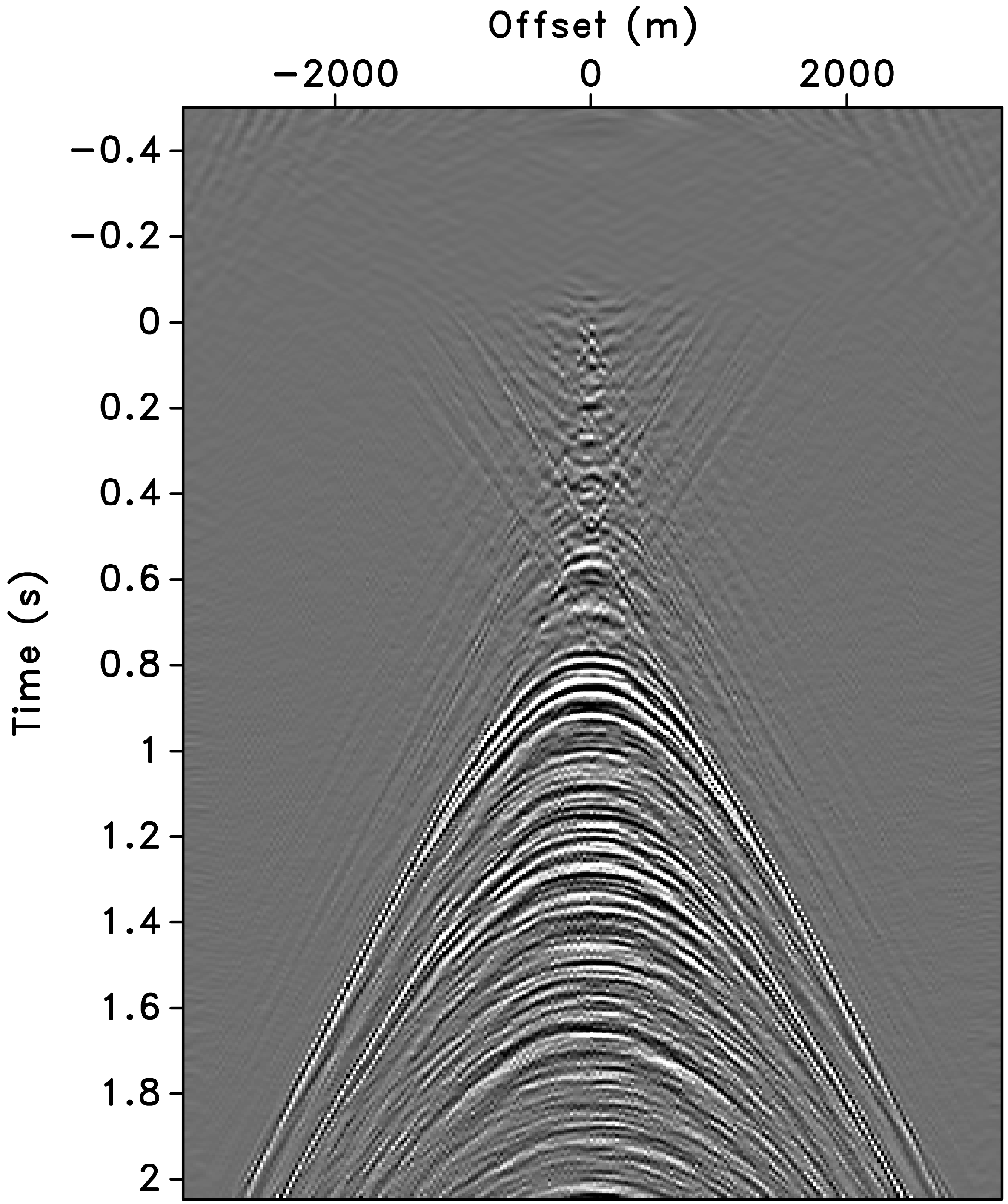
$$\begin{cases} \mathbf{U} & = \Delta \mathbf{P}^H & \text{(adjoint primary data-matrix operator)} \\ \mathbf{V} & = \mathbf{P} & \text{(total data)} \\ \mathbf{b} & = \text{vec}\,(\mathbf{V}) & \\ \mathbf{A} & = \mathbf{U}\mathbf{S}^H & \text{(multi-D correlation)} \\ \mathbf{S}^H & = \mathbf{C}_3^H & \text{(3-D curvelet transform)} \\ \tilde{\mathbf{x}} & = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \|\mathbf{A}\mathbf{x} - \mathbf{b}\|_2 \leq \epsilon & \\ \tilde{\mathbf{P}} & = \text{vec}^{-1}\left(\mathbf{S}^H \tilde{\mathbf{x}}\right) & \text{(recovered data)} \end{cases}$$

- Defocusing by *inversion* of the ***adjoint*** of *primary-data matrix operator*
- Multi-D *deconvolution* of the multi-D *correlation* with the *primaries*
- Reconstruction by *inverse* curvelet transform

Defocussed multiple prediction

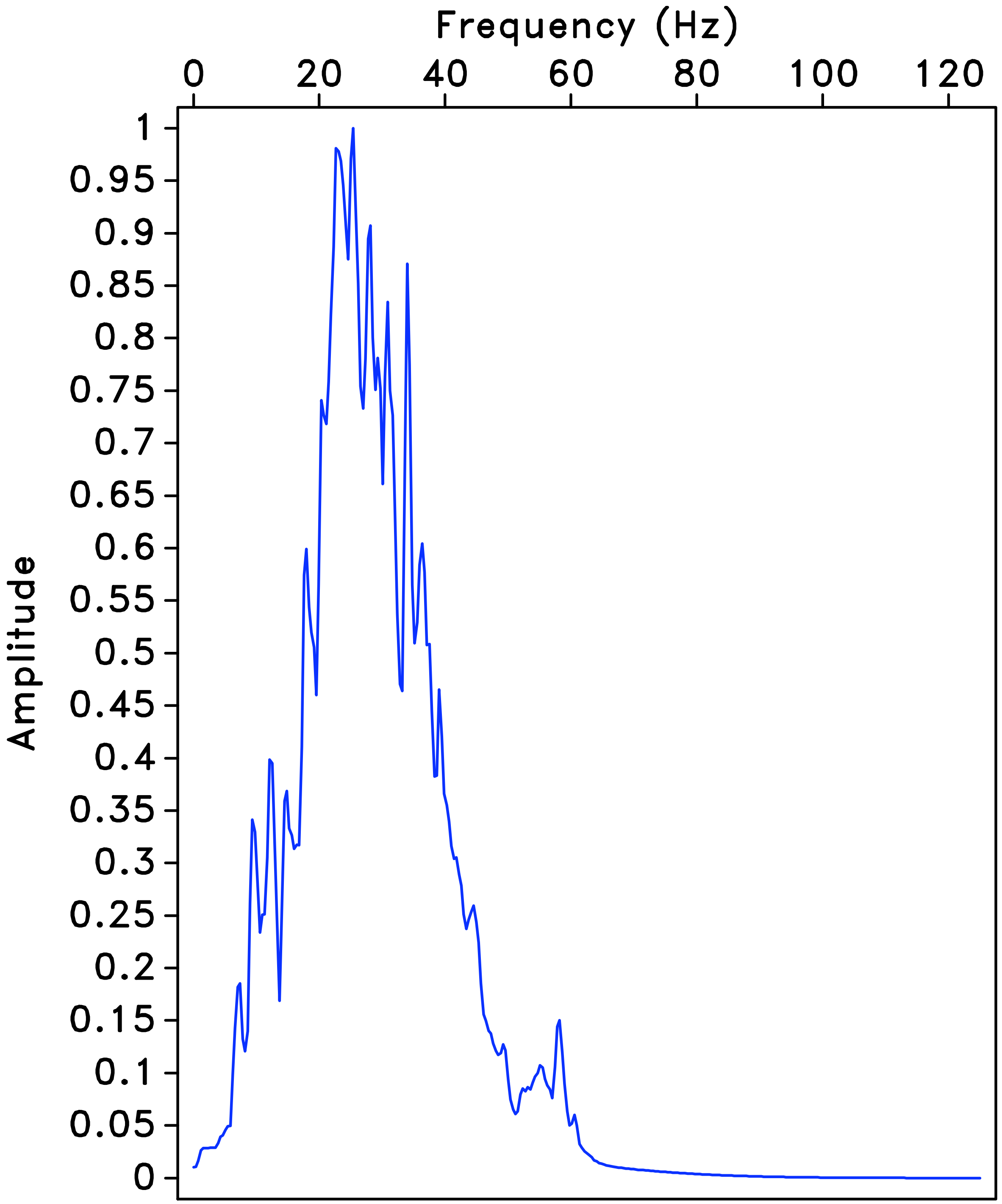


multi-D convolution

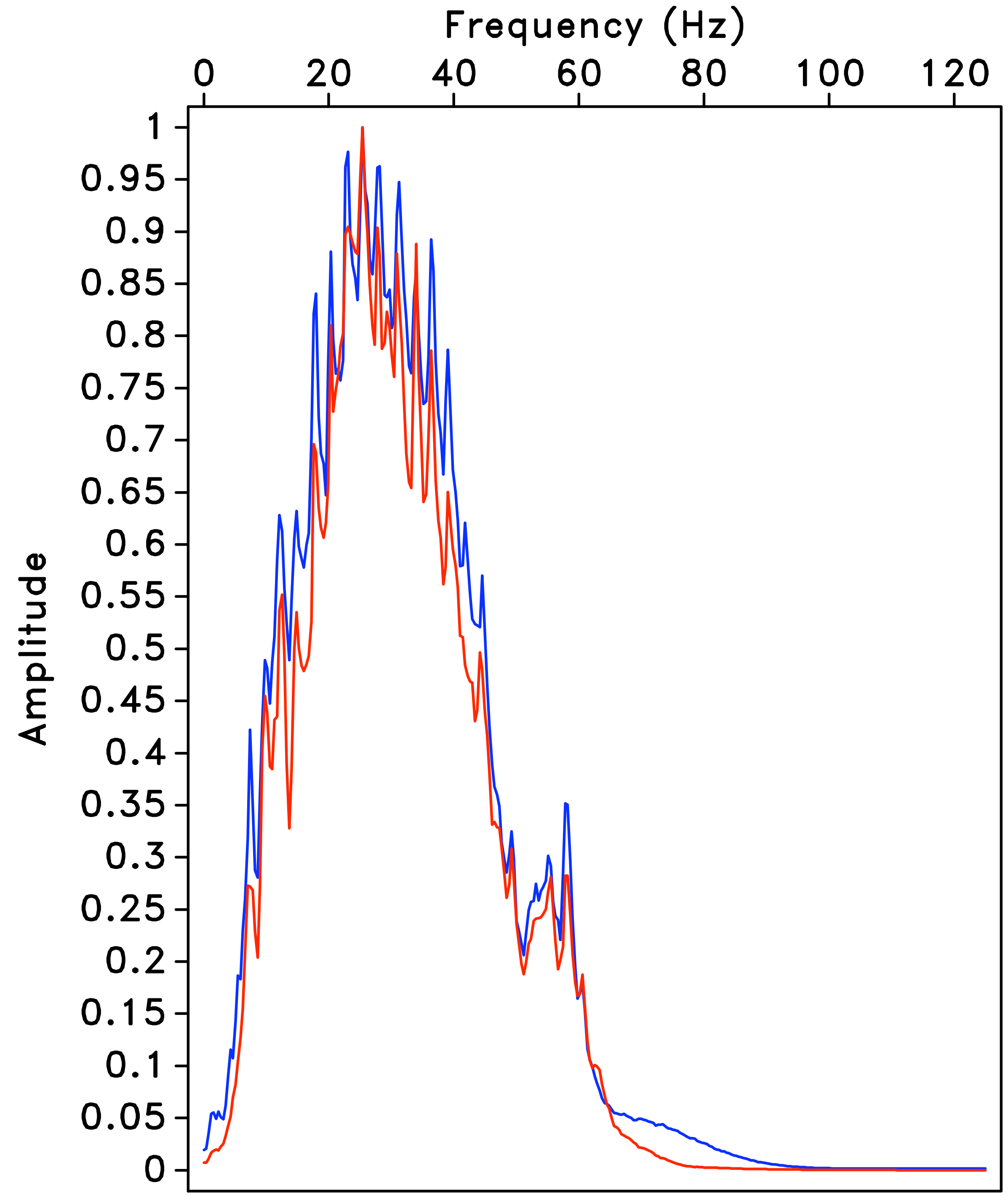


multi-D deconvolution

Amplitude spectra (averaged)

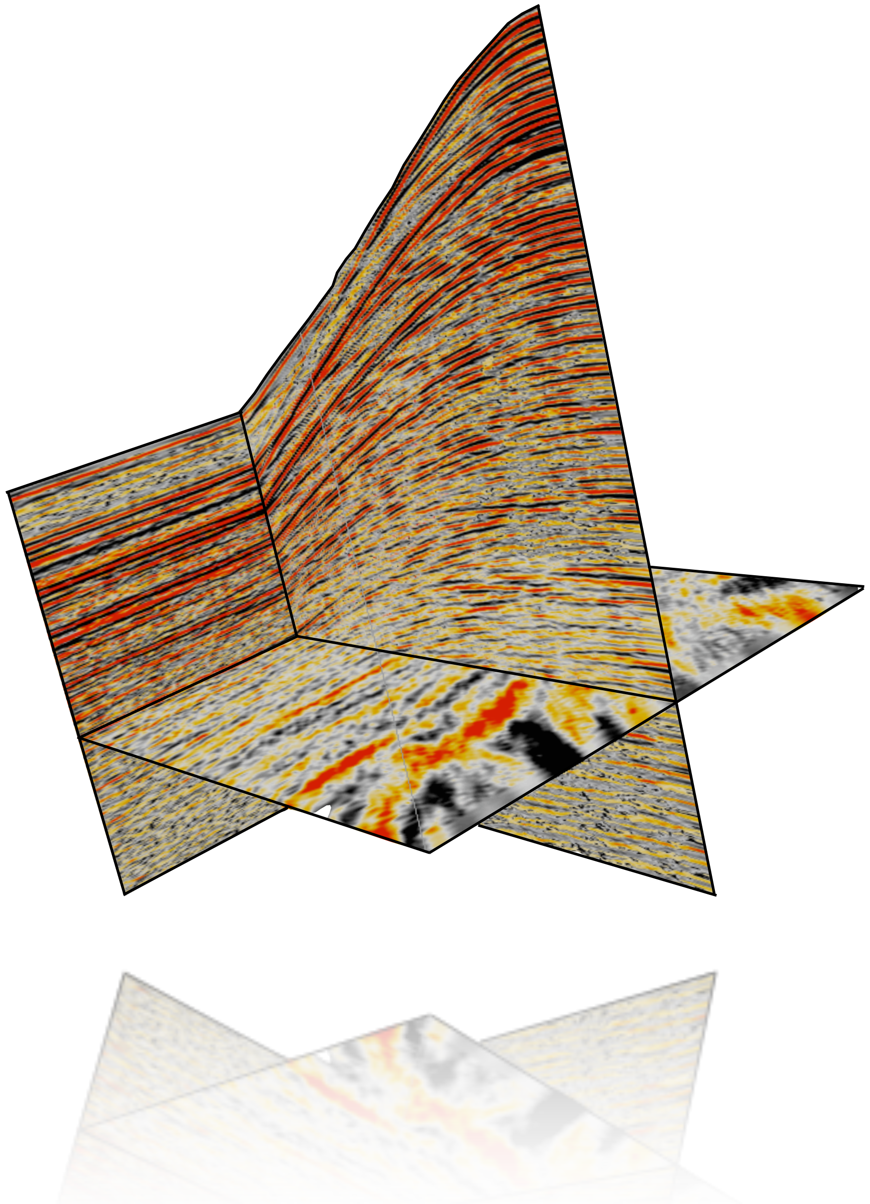


multi-D convolution



multi-D deconvolution

Stable computation of the ‘data inverse’



SEG
Las Vegas, November 9-14

Motivation

- *Data-matrix inverse domain* leads to a natural separation of *primaries* and *surface-related multiples* [Berkhout '06]

$$\hat{\mathbf{P}}^{\dagger} = \mathbf{\Delta}\hat{\mathbf{P}}^{\dagger} - \hat{\mathcal{A}},$$

inverted data — inverted primaries — 'source'

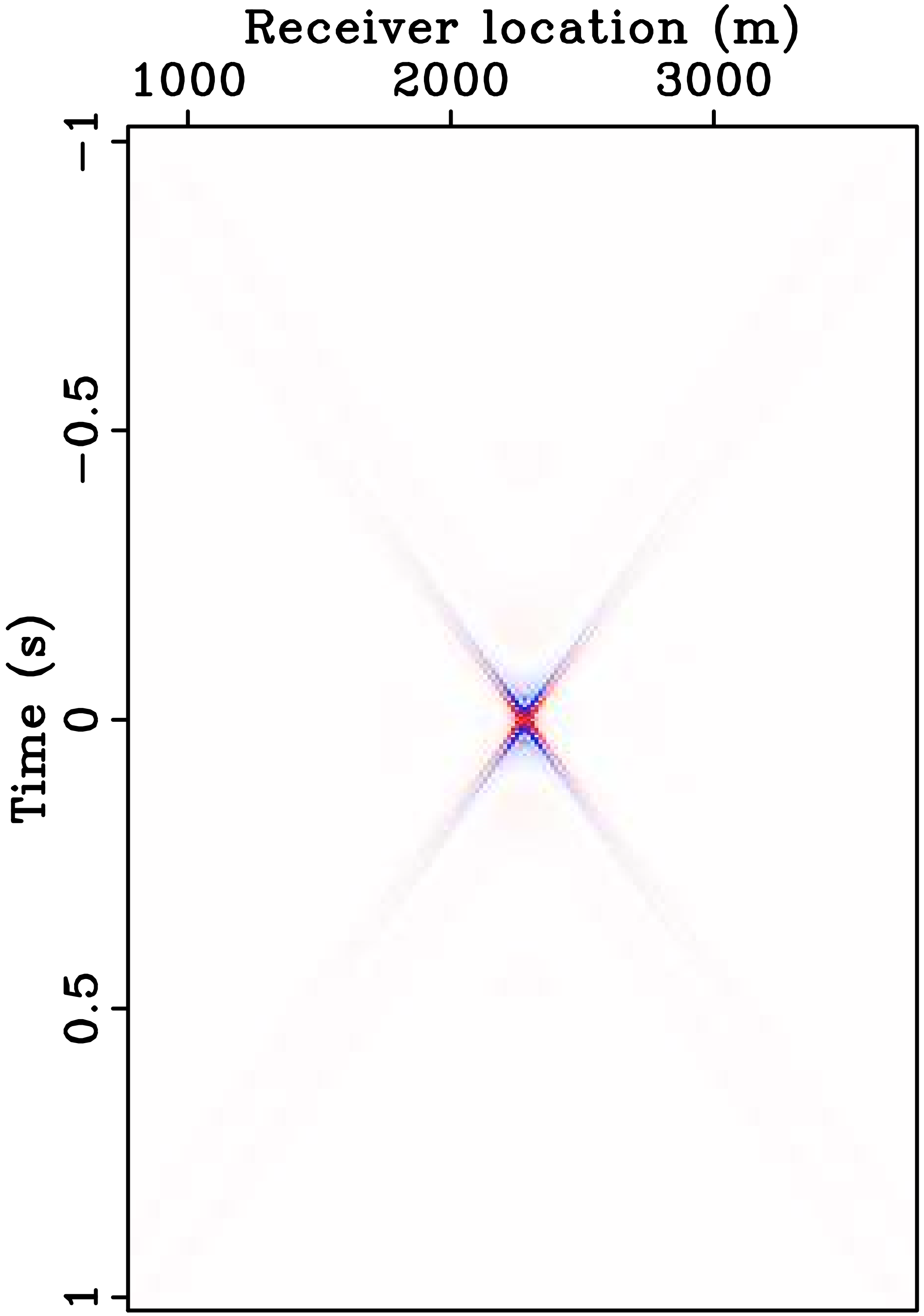
  - surface-related effects including source signature are mapped to a directional source
  - primaries are mapped to the inverse of the primary data matrix

- Application to *real* data hampered by instabilities ...

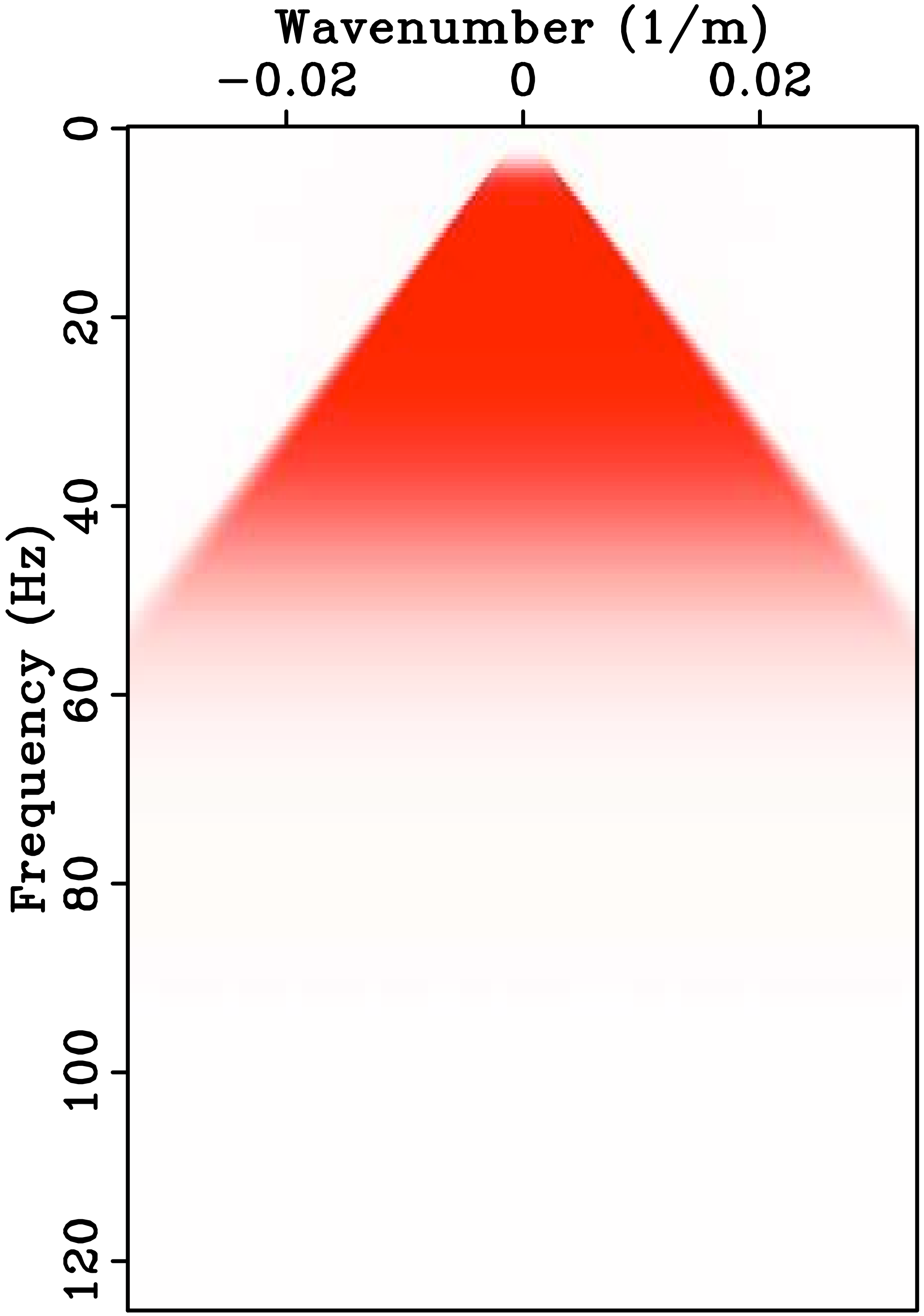
Data inverse

$$
\begin{cases}
\mathbf{U} & = \mathbf{P} & \text{(total data operator)} \\
\mathbf{V} & = \mathbf{I}_{\Psi} & \text{(bandwidth-limited delta)} \\
\mathbf{b} & = \operatorname{vec}(\mathbf{V}) & \\
\mathbf{A} & = \mathbf{U}\mathbf{S}^{H} & \text{(multi-D convolution)} \\
\mathbf{S}^{H} & = \mathbf{C}_{3}^{H} & \text{(3-D curvelet transform)} \\
\tilde{\mathbf{x}} & = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \|\mathbf{A}\mathbf{x}-\mathbf{b}\|_2 \leq \epsilon & \\
\tilde{\mathbf{P}} & = \operatorname{vec}^{-1}\left(\mathbf{S}^{T}\tilde{\mathbf{x}}\right) & \text{(inverted data)}
\end{cases}
$$

- Inversion of the *full-data matrix operator*
- Multi-D *deconvolution* of the multi-D *convolution* with the data
- Regularized by curvelet-domain *sparsity* promotion

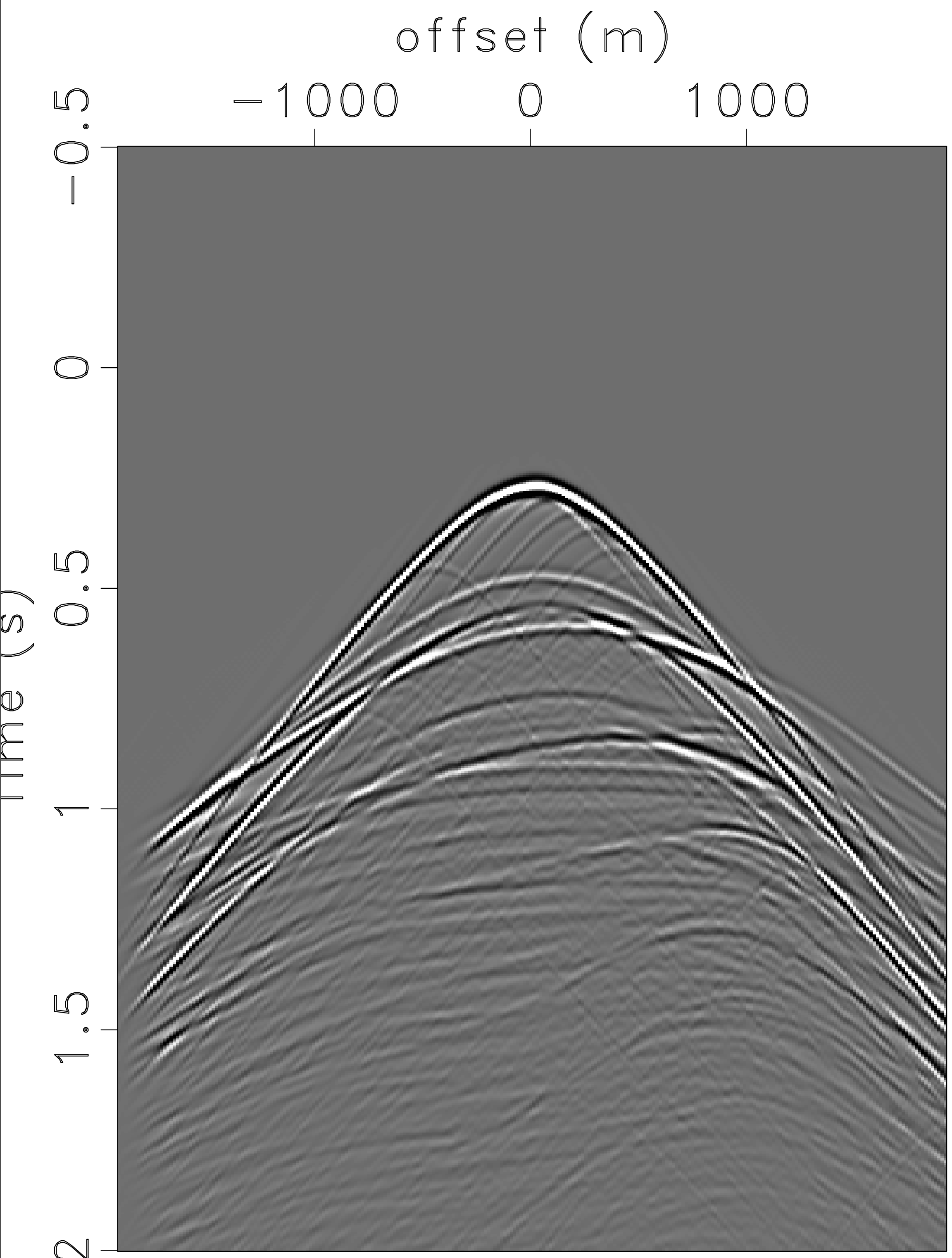


bandwidth-limited pulse

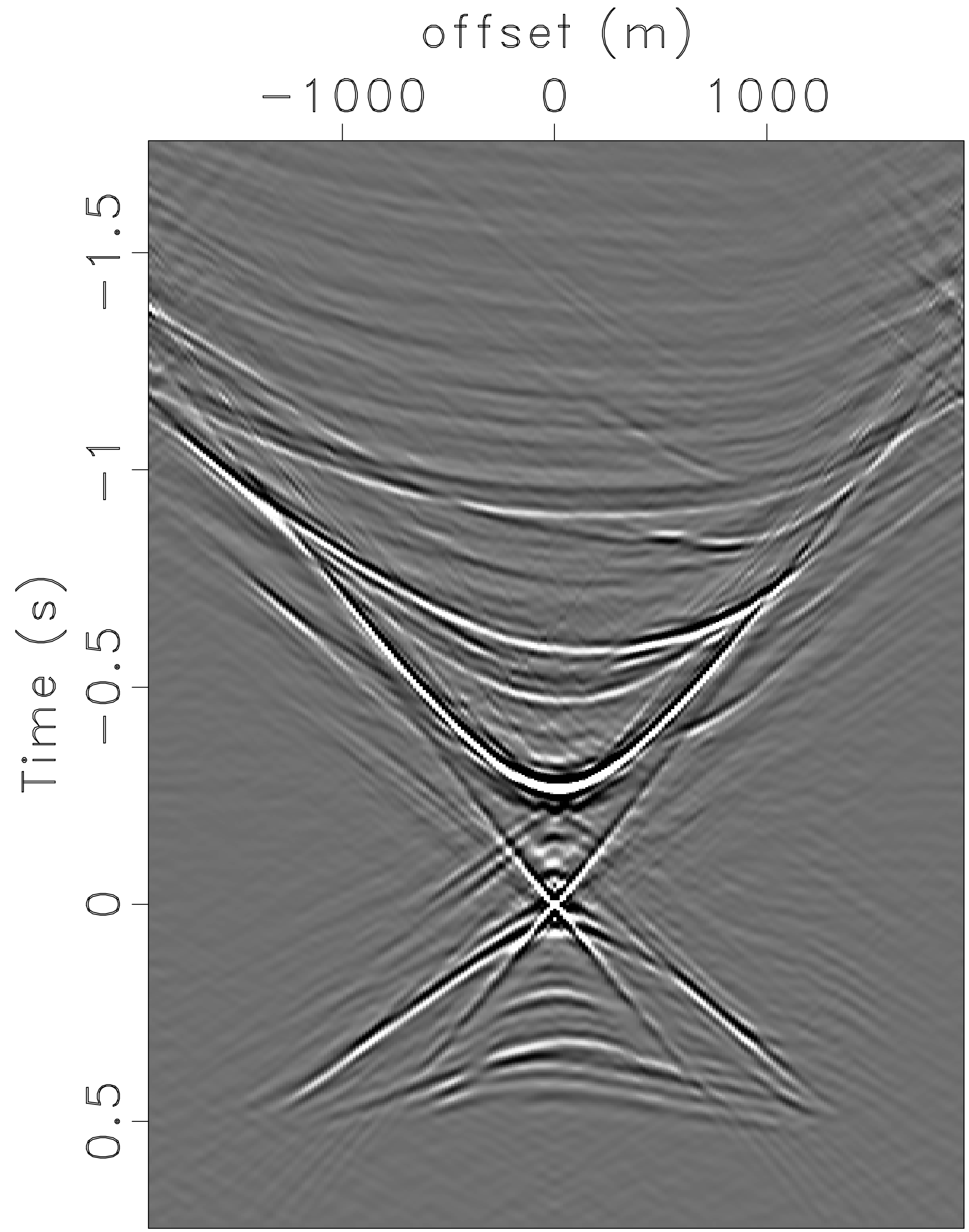


the same in f-k space

Data inverse synthetic data

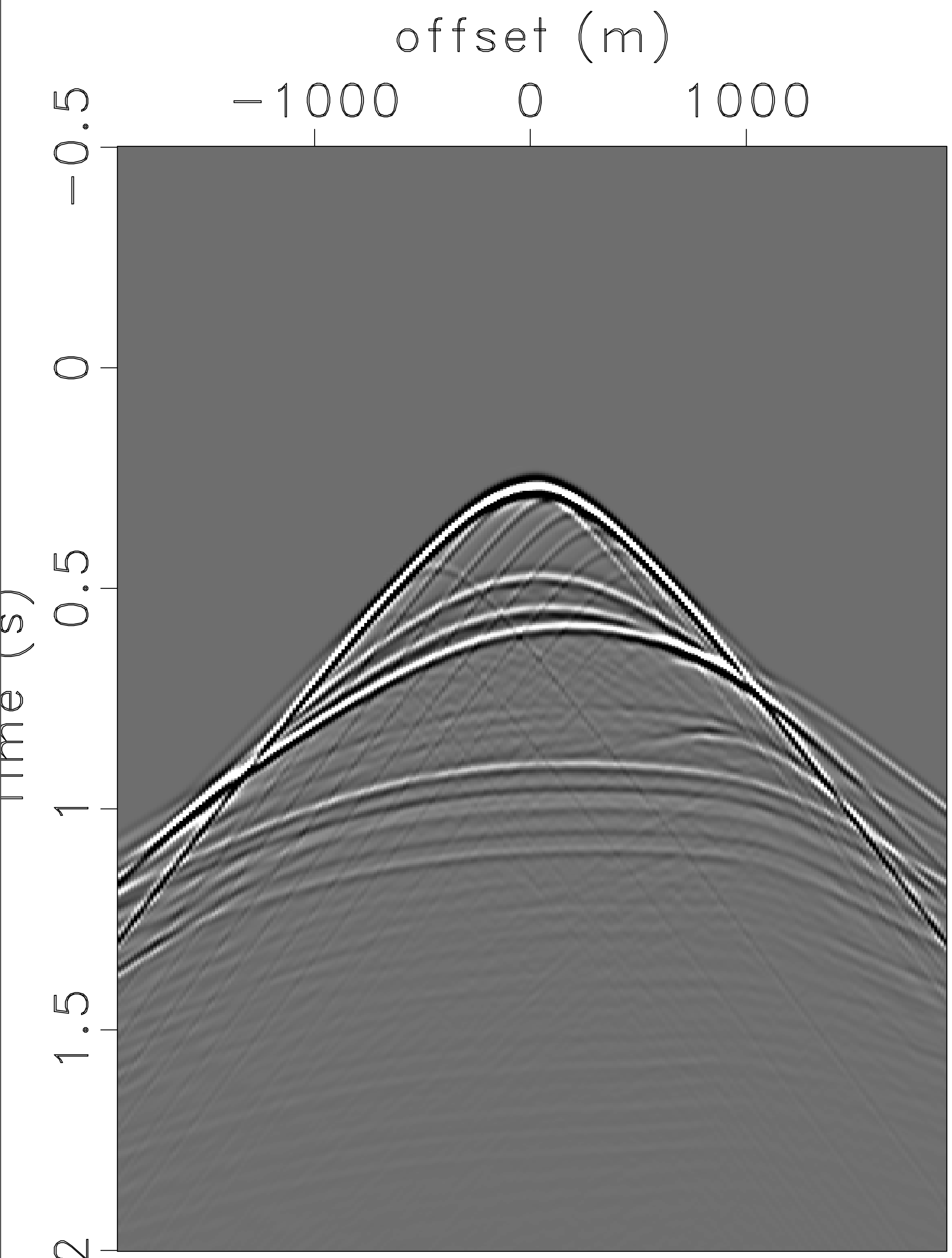


total data

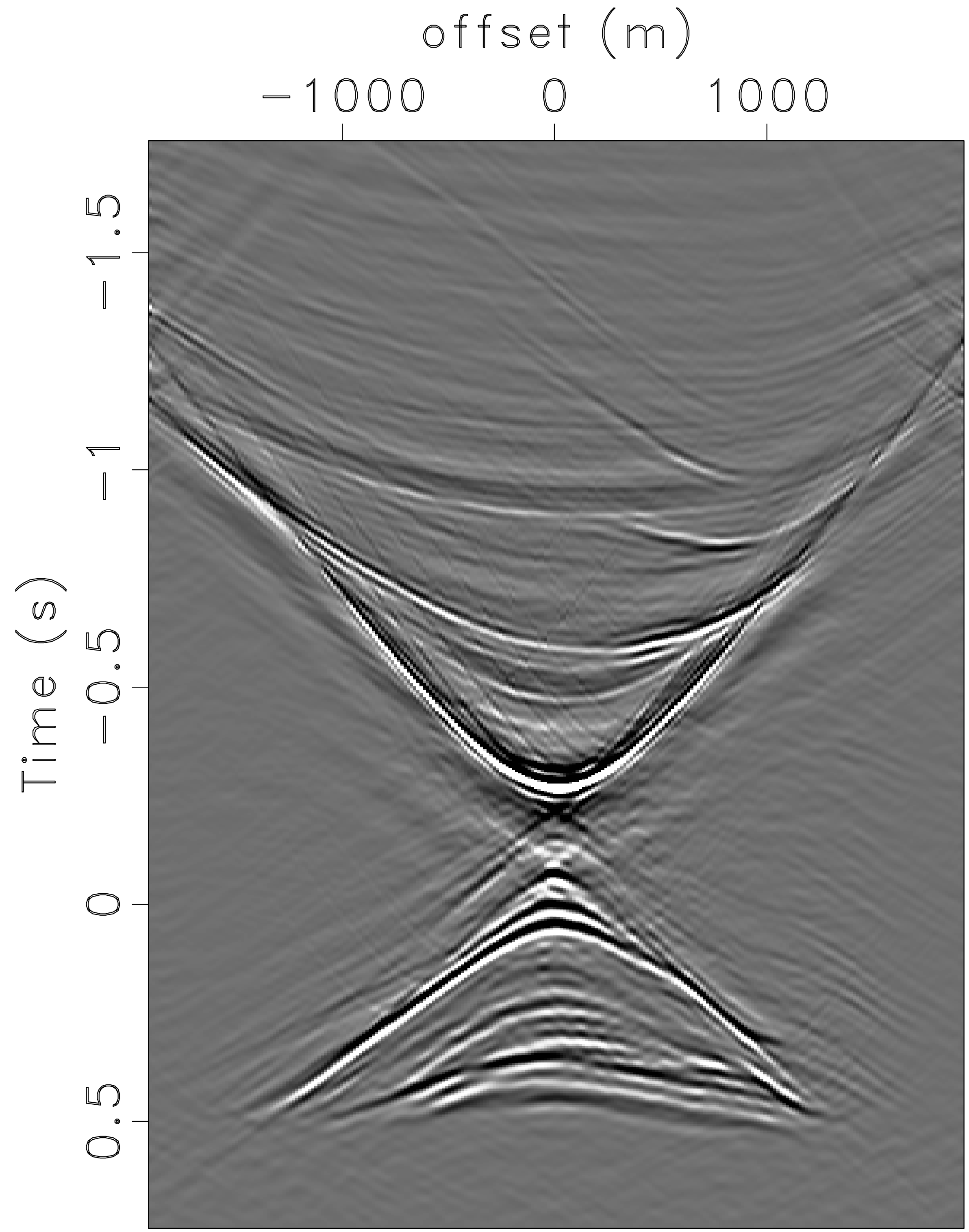


total data inverse

Data inverse synthetic data

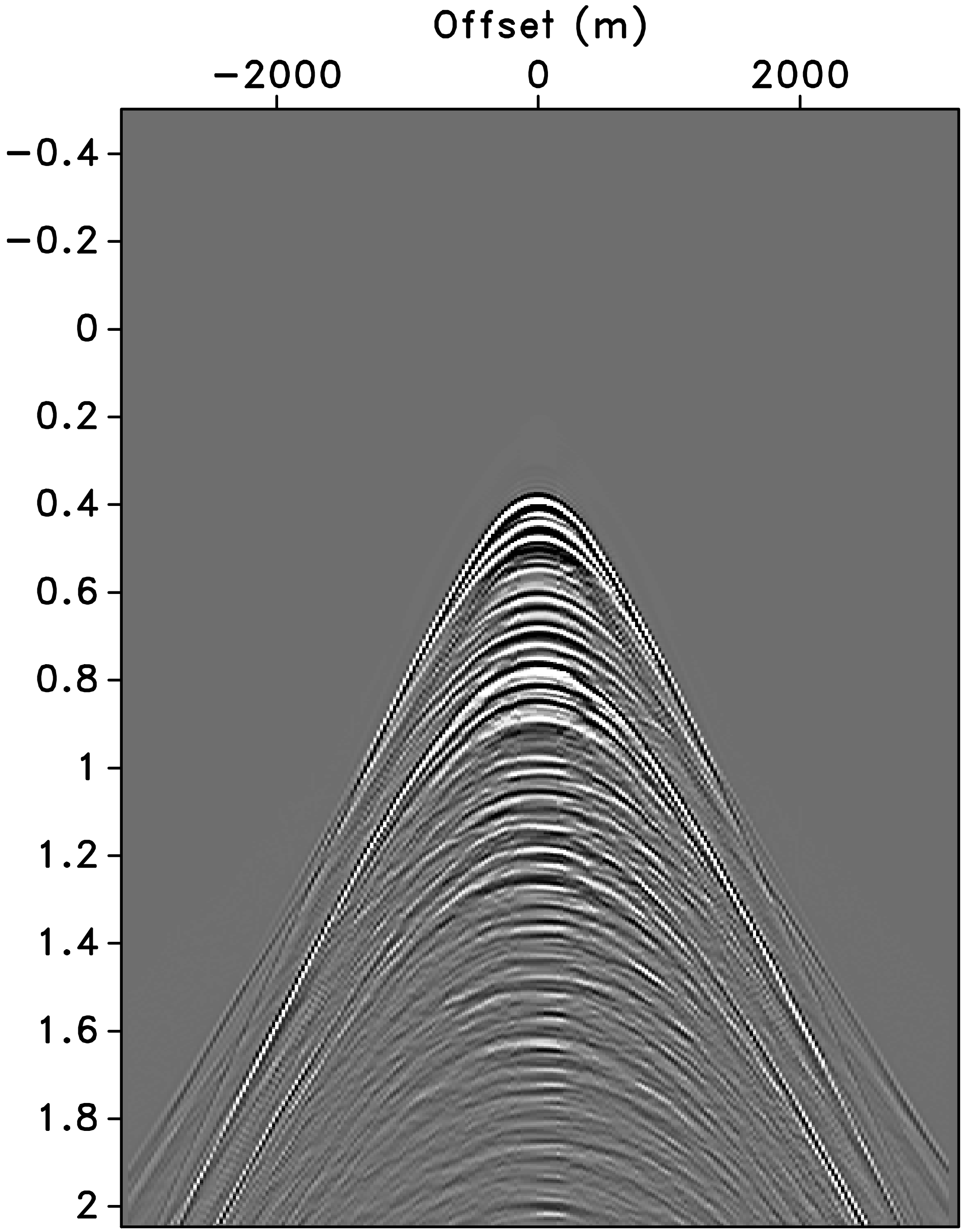


estimated primaries

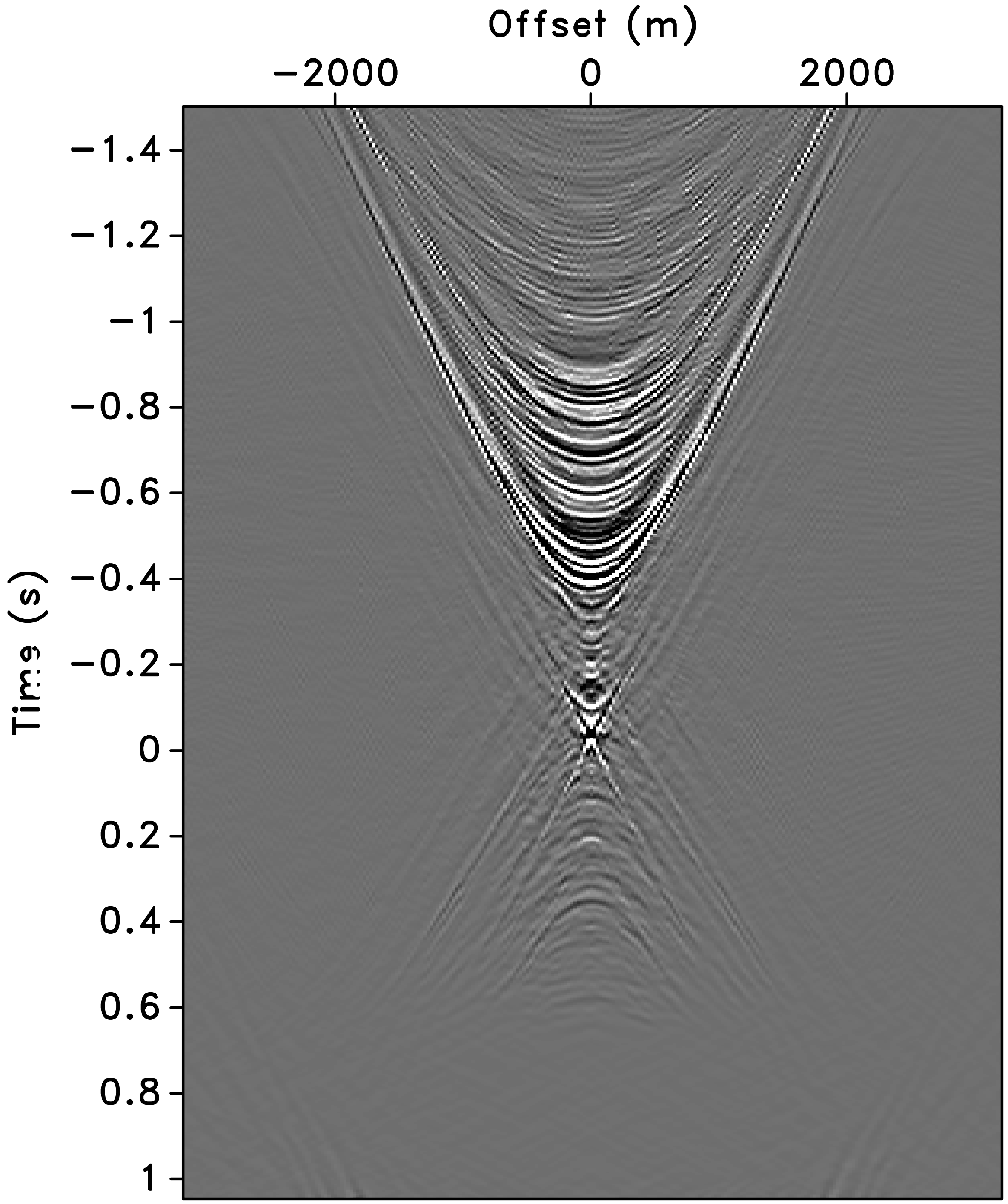


estimated-primaries inverse

Data inverse real data

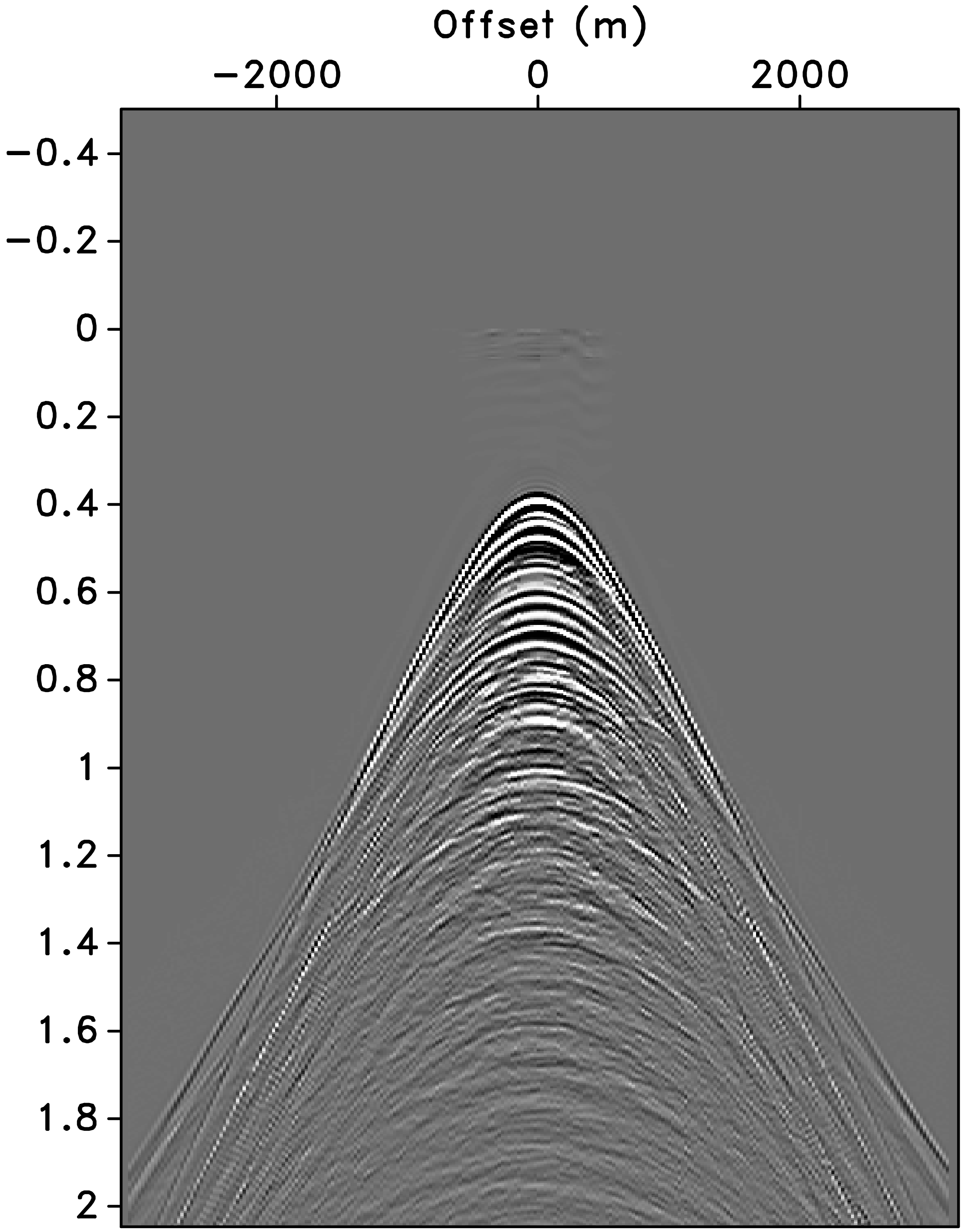


total data

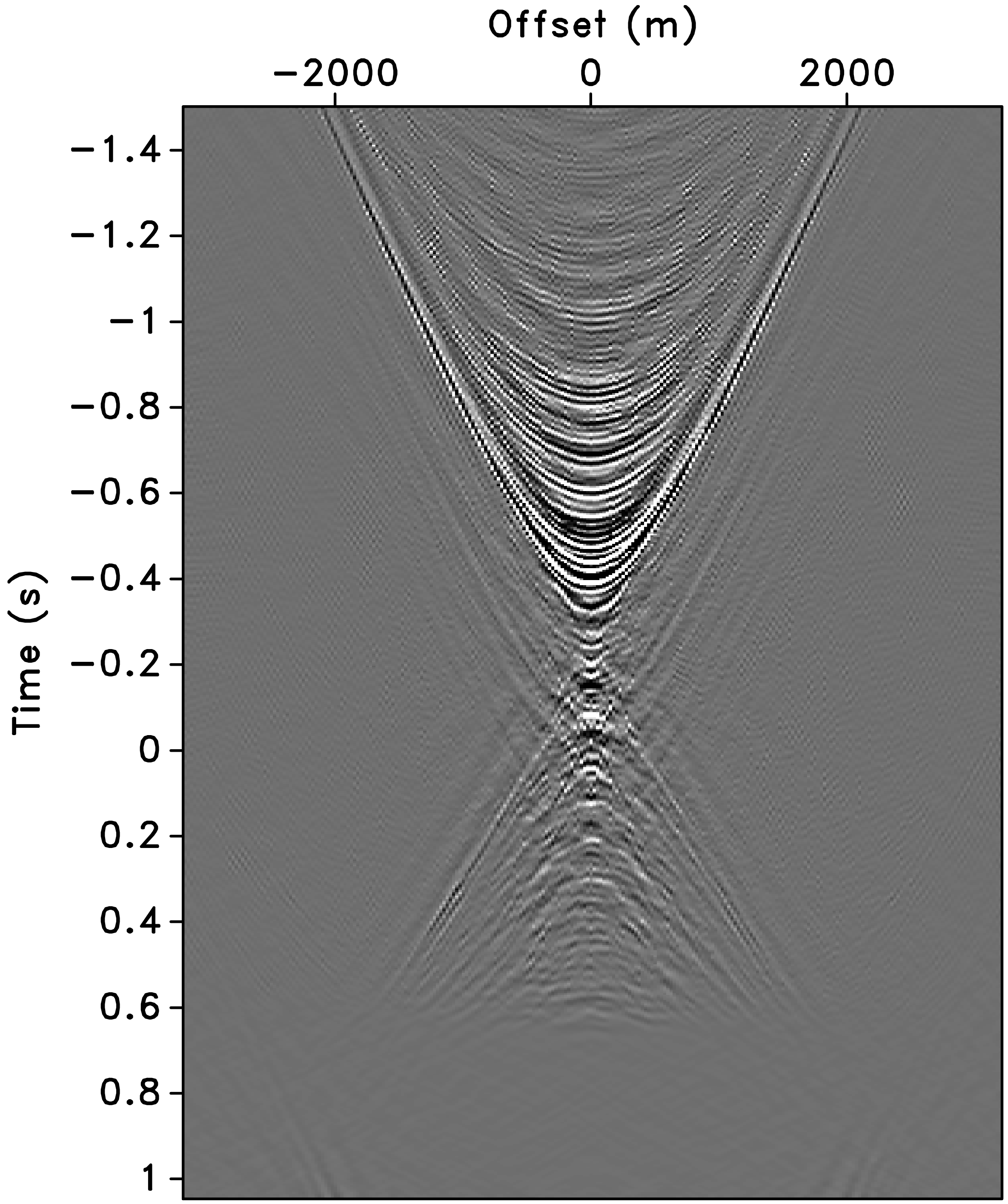


total-data inverse

Data inverse real data

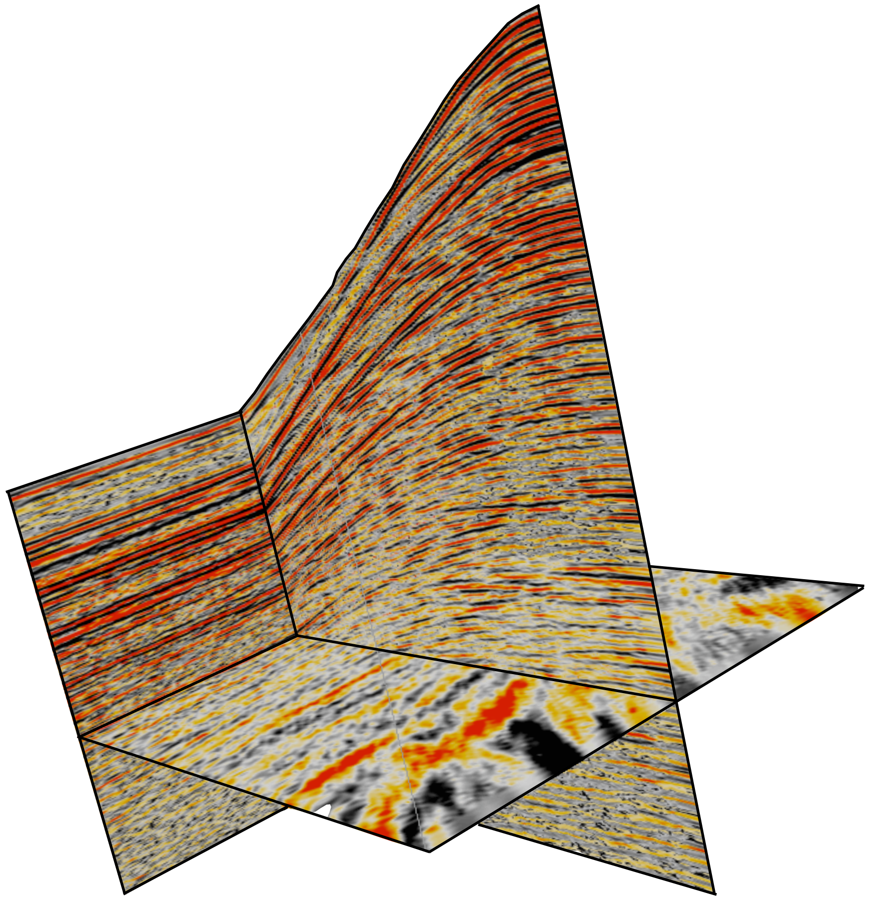


estimated primaries



estimated-primaries inverse

An encore: imaging of blended data



SEG
Las Vegas, November 9-14

Motivation

- **Observation:** *Blended* data acquisition is an instance of *compressive sensing* [F.J.H et. al ‘08]

- *Image **directly*** in the *simultaneously* acquired data domain

- Imaging conditions associated with adjoint-state methods [Tarontola ‘80s, Plessix, Pratt ’00’s] for the wave equation are based on multi-D correlations of wavefields
  - suffer from finite aperture & source effects
  - contain interferences due to blended acquisition

- Alternative approach based on *wavefield inversion*

Adjoint state or reverse-time methods

- At each depth level multi-D correlation of the monochromatic forward and inverse extrapolated wavefields, **U** and **V**
- Zero-offset image [Berkhout, Claerbout, and others, ‘80s]

$$\boldsymbol{\delta}\mathbf{m} \approx \mathrm{diag}\left(\Re\left(\hat{\mathbf{U}}\hat{\mathbf{V}}^{*}\right)\right)$$

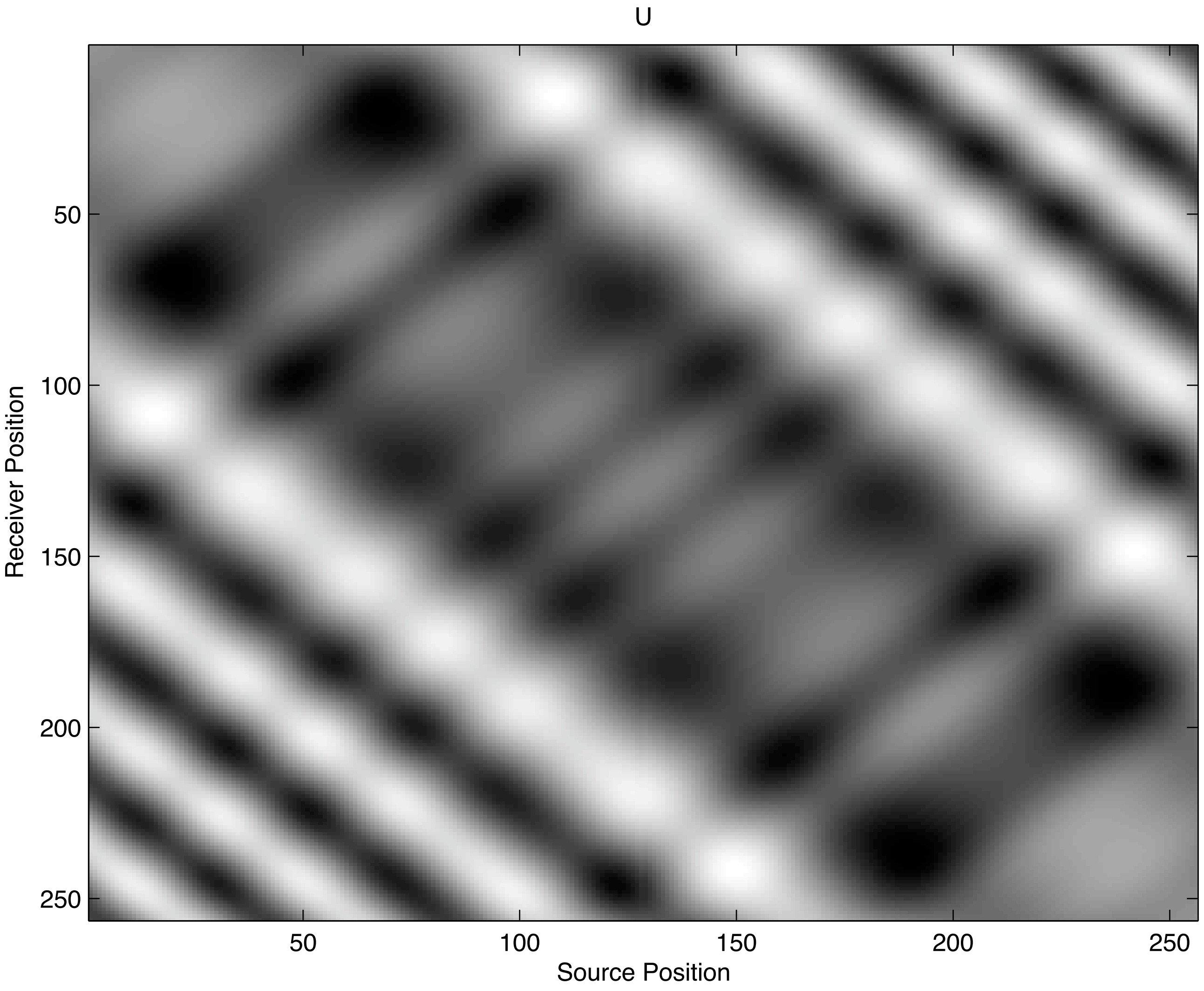
- Consider deconvolution instead, i.e,

$$\hat{\mathbf{G}} = \Re\left(\hat{\mathbf{U}}\hat{\mathbf{V}}^{\dagger}\right)$$

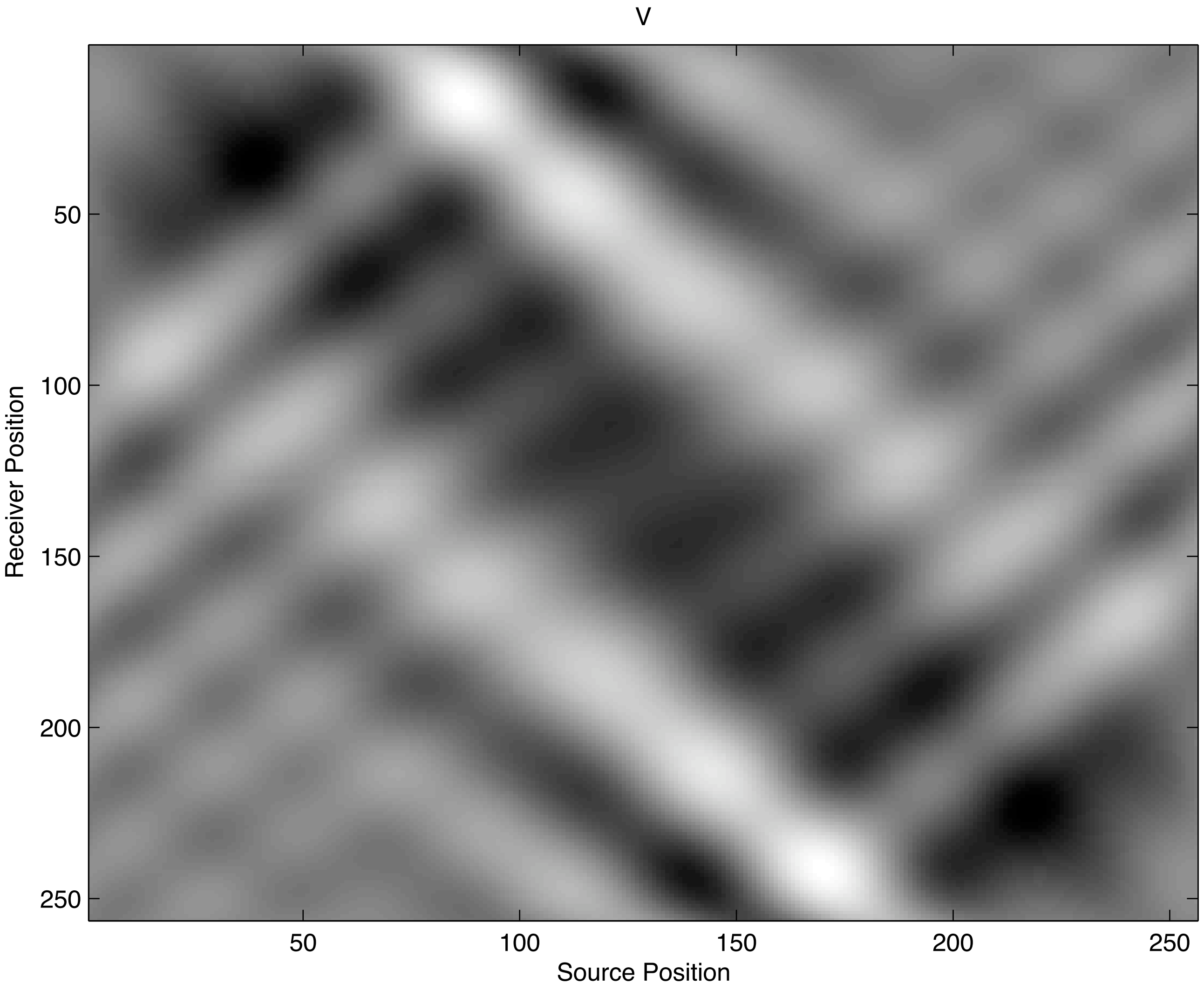
- Use wavefield inversion technique
  - improve imaging
  - recover from blended data = compressively subsampled data

Wavefields at 30 Hz [real parts]

$\hat{\mathbf{U}}$



$\hat{\mathbf{V}}$



Imaging by deconvolution

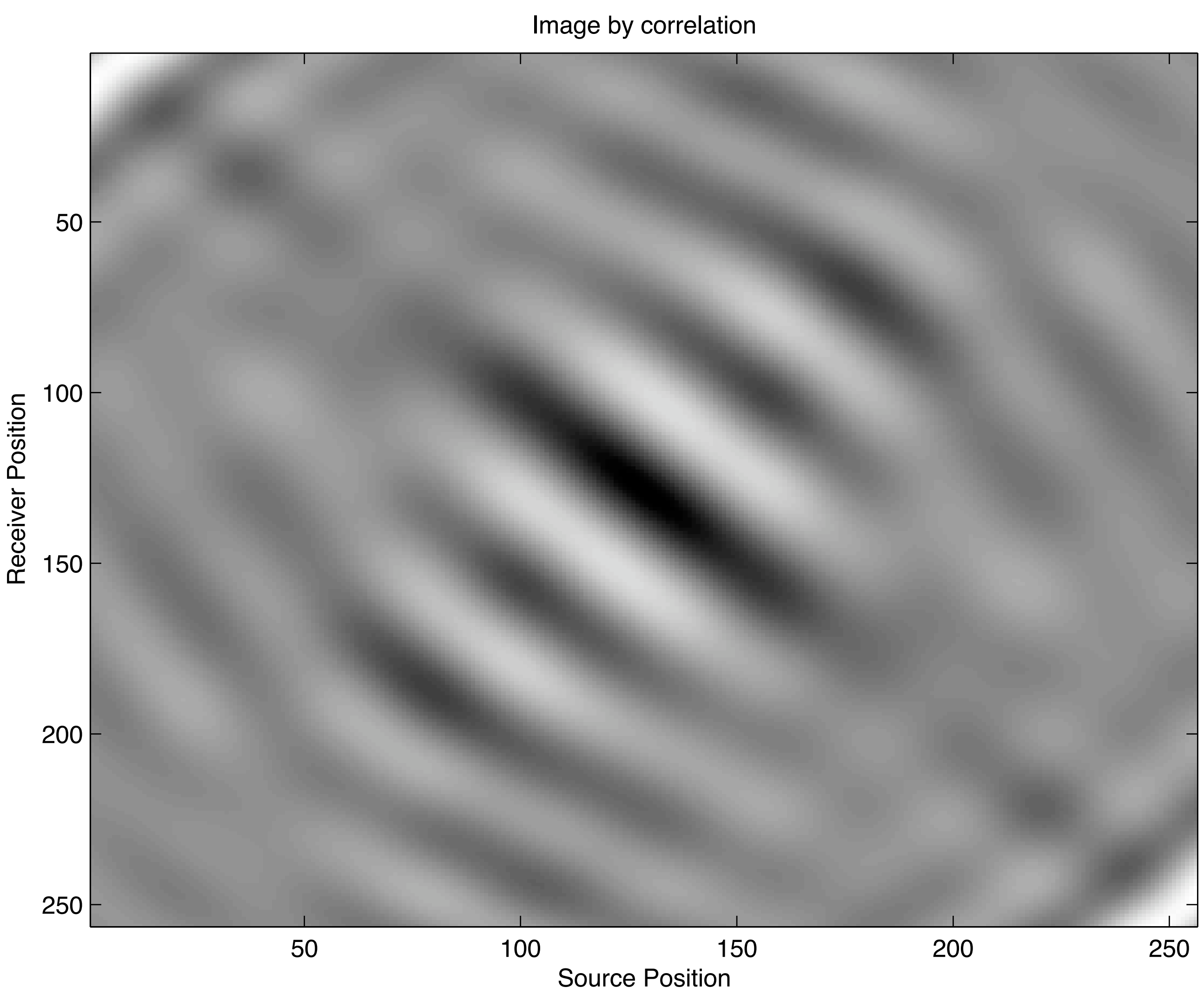
$$\begin{cases} \mathbf{b} &= \text{vec}\left(\hat{\mathbf{V}}^H\right) \\ \mathbf{A} &= \hat{\mathbf{U}}^H \mathbf{C}_2^H & \text{(focused 2-D curvelet transform)} \\ \tilde{\mathbf{x}} &= \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \|\mathbf{A}\mathbf{x} - \mathbf{b}\|_2 \le \epsilon \\ \tilde{\mathbf{G}} &= \text{vec}^{-1}\left(\mathbf{C}_2^H \tilde{\mathbf{x}}\right) & \text{(imaged data)} \end{cases}$$

- *Inversion* instead of *correlation*
- Regularized by 2-D curvelet sparsity promotion
- Example for single layer model at transition

Correlation-based versus wavefield inversion

$$\hat{\mathbf{G}} = \Re\left(\hat{\mathbf{U}}\hat{\mathbf{V}}^{\dagger}\right)$$

$$\tilde{\mathbf{G}} = \mathrm{vec}^{-1}\left(\mathbf{C}_2^H \tilde{\mathbf{x}}\right)$$



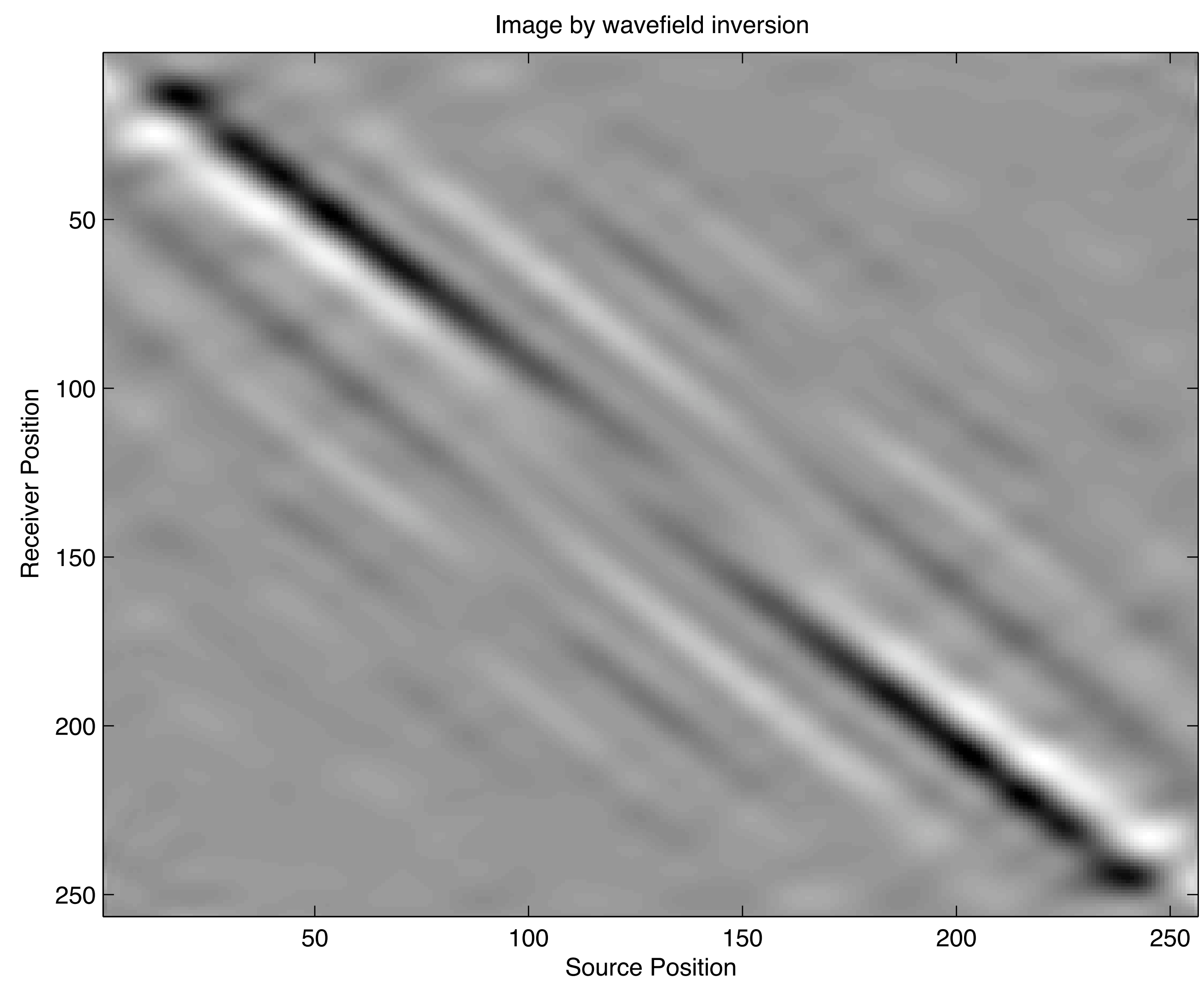


Image by correlation

Image by deconvolution

Imaging of blended data

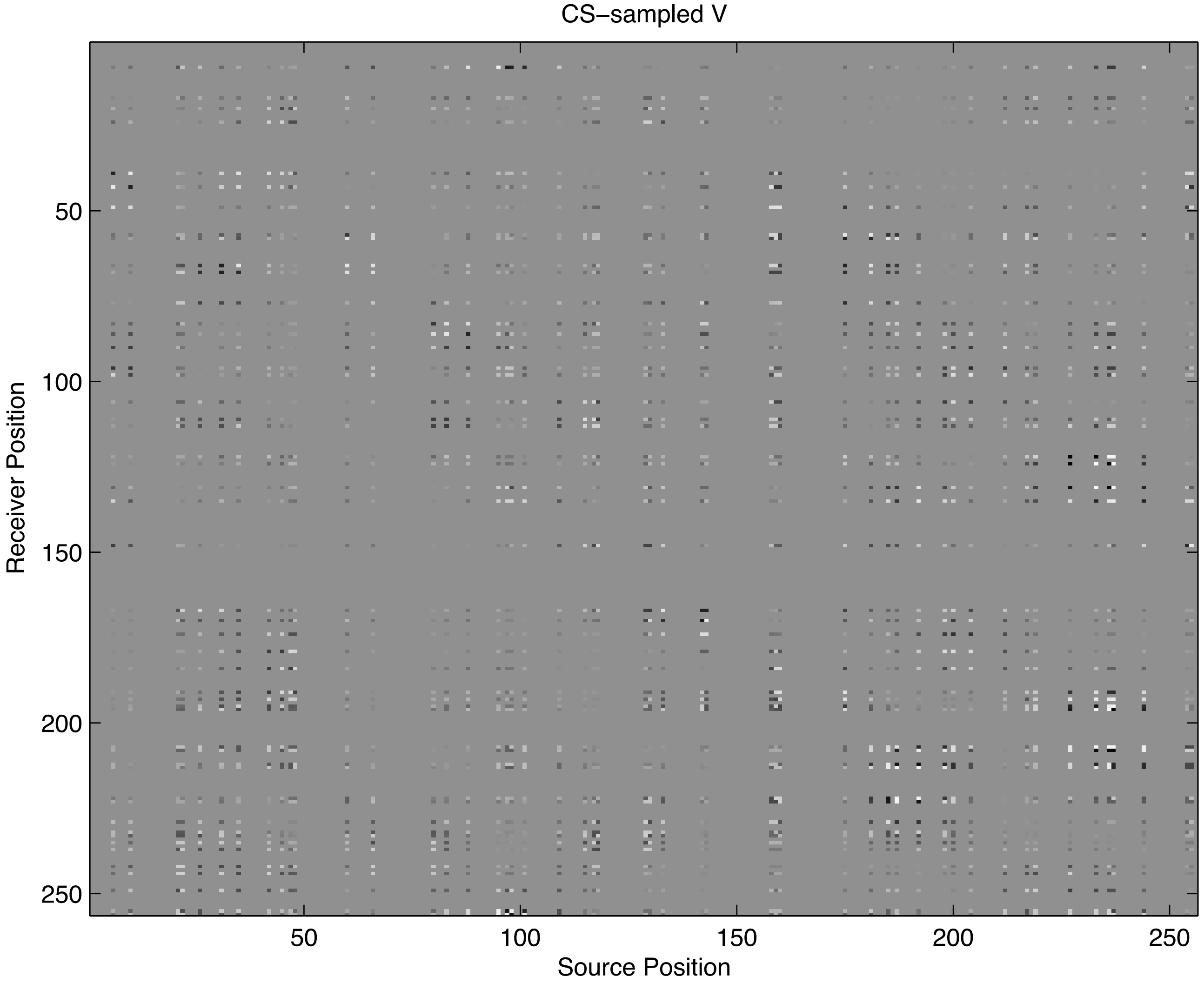
$$
\begin{cases}
\mathbf{R} & = \left(\mathbf{R}^{\Sigma_s} \otimes \mathbf{R}^{\Sigma_r}\right) & \text{(picking operator)} \\
\mathbf{M} & = \mathbf{F}_2^* \left(e^{\hat{i}\boldsymbol{\theta}}\right) \mathbf{F}_2 & \text{(random encoder)} \\
\mathbf{b} & = \mathbf{R}\mathbf{M}\text{vec}\left(\hat{\mathbf{V}}\right) & \text{(blended wavefield)} \\
\mathbf{A} & = \mathbf{R}\mathbf{M}\hat{\mathbf{U}}^H \mathbf{C}_2^H & \text{(blended focused 2-D curvelet transform)} \\
\tilde{\mathbf{x}} & = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \|\mathbf{A}\mathbf{x} - \mathbf{b}\|_2 \leq \epsilon \\
\tilde{\mathbf{G}} & = \text{vec}^{-1}\left(\mathbf{C}_2^H \tilde{\mathbf{x}}\right) & \text{(imaged data)}
\end{cases}
$$

with $\boldsymbol{\theta} = \text{Uniform}([0, 2\pi])$ random phase rotations.

- CS subsampling after Romberg's ['08] random convolution
- Regularized by 2-D curvelet sparsity promotion
- Imaged from *source-receiver down-sampling* after Fourier-space random phase encoding

Imaging of blended data

$$\mathrm{vec}^{-1}\left(\mathbf{R}\mathbf{M}\mathrm{vec}\left(\hat{\mathbf{V}}\right)\right)$$



Subsampled V

$$\mathrm{vec}^{-1}\left(\mathbf{A}^{H}\mathbf{b}\right)$$

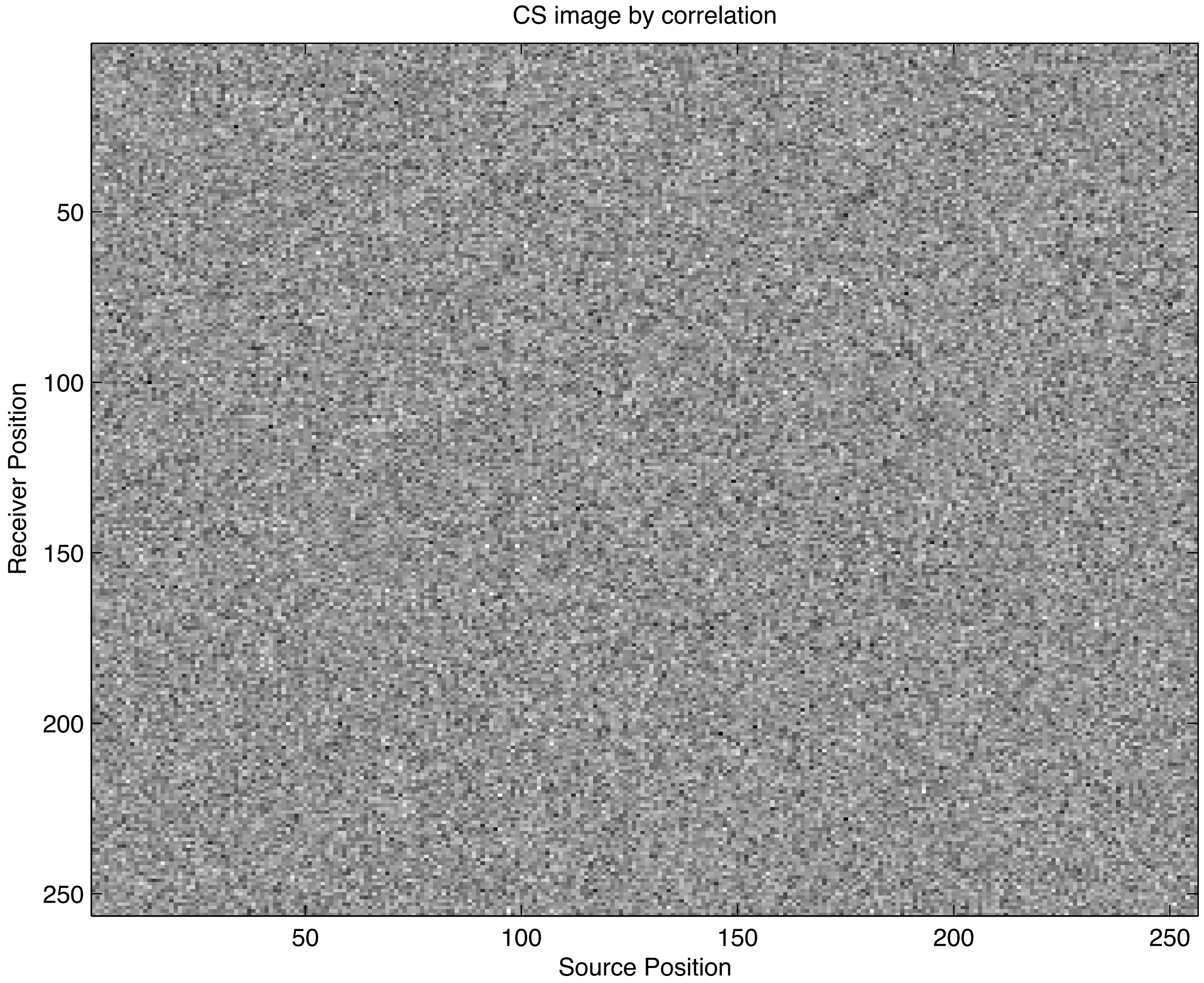


Image by correlation

Imaging of blended data

$$\tilde{\mathbf{G}} = \mathrm{vec}^{-1}\left(\mathbf{C}_2^H \tilde{\mathbf{x}}\right)$$

$$\mathrm{diag}\left(\Re\left(\tilde{\mathbf{G}}\right)\right)$$

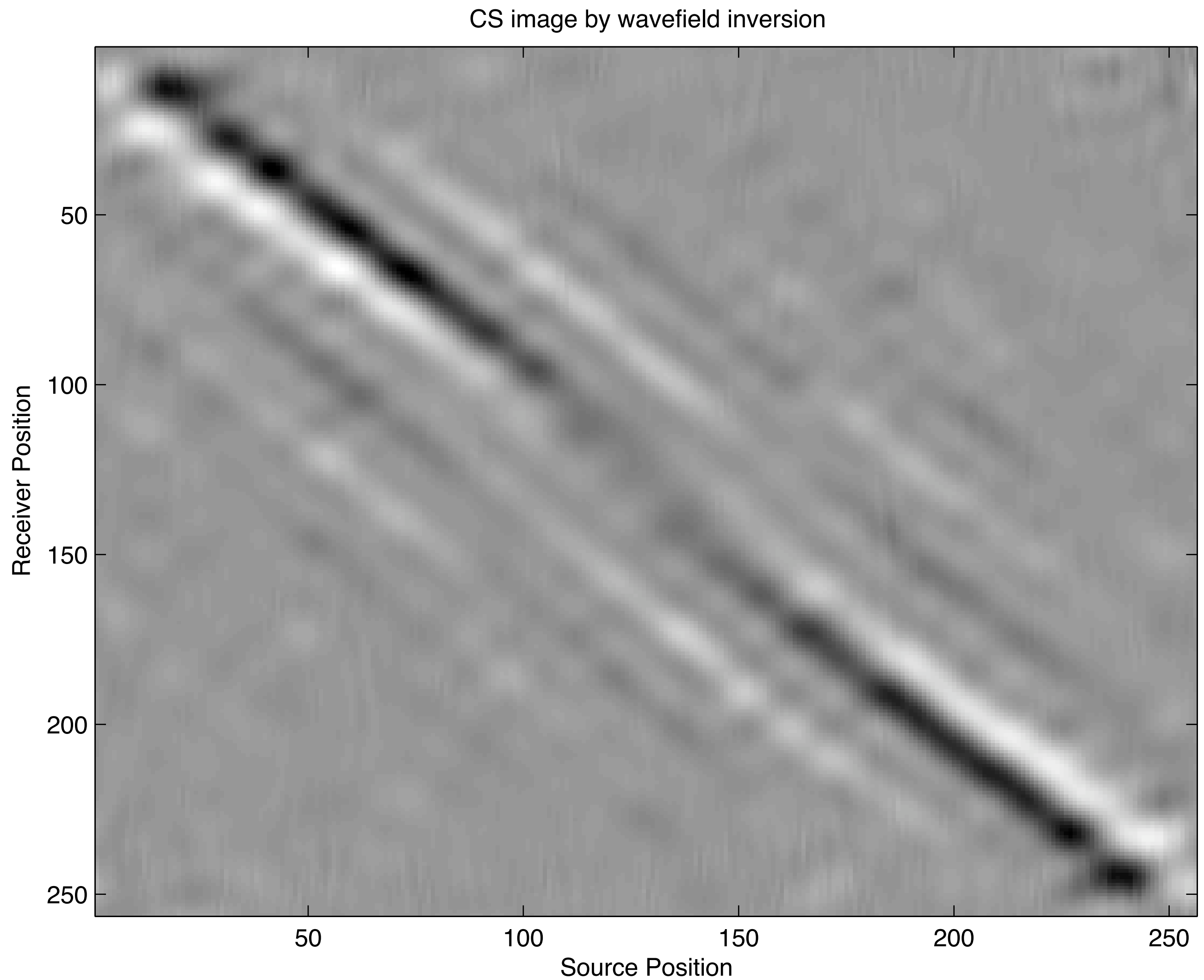
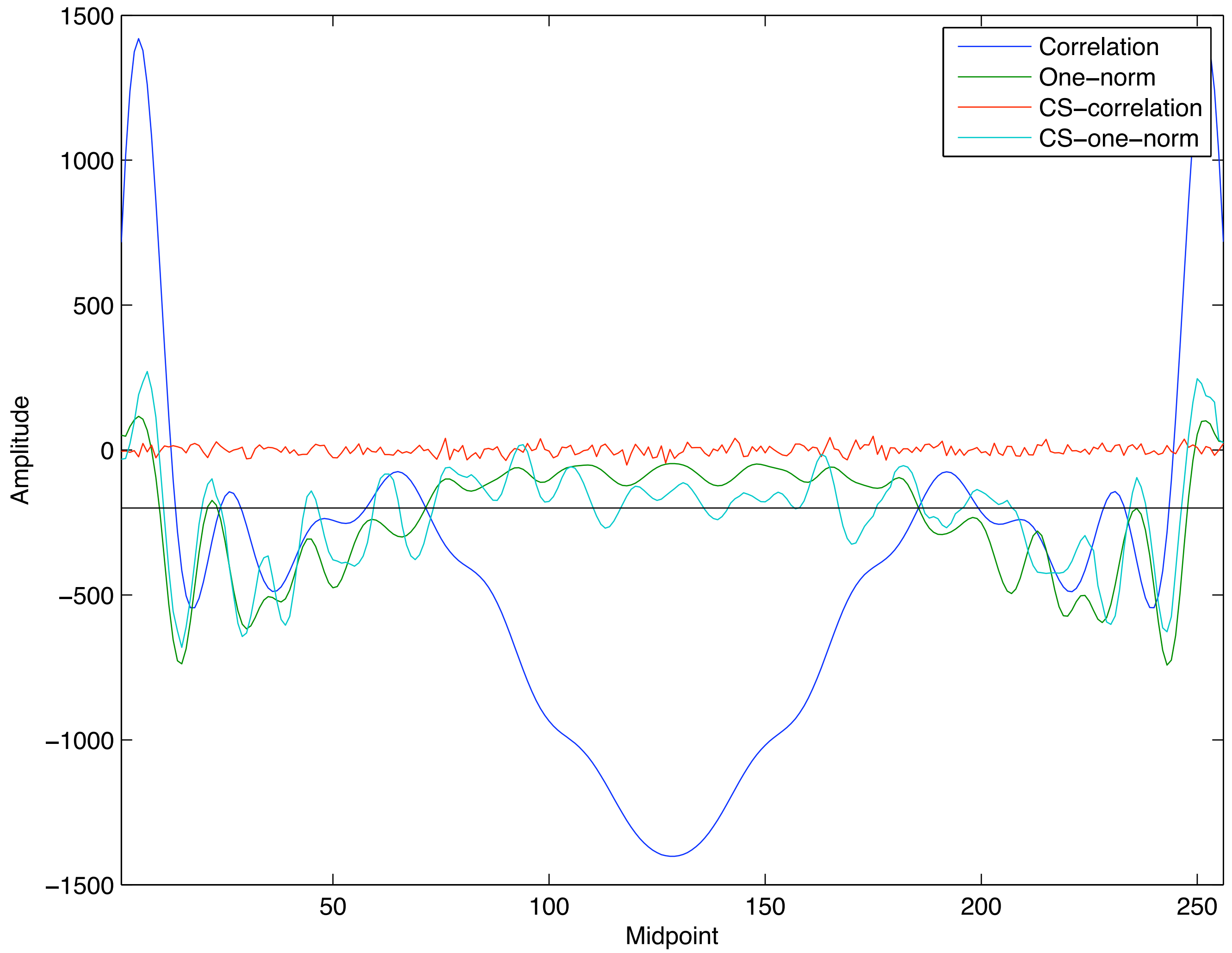


Image by deconvolution



Comparison

Conclusions

- Wavefield inversion is a versatile tool in seismic-data processing & imaging
- Curvelet-domain sparsity is a powerful *prior* that leads to *stable* inversions of
  - the primary-matrix operator => improved focusing & recovery
  - the adjoint of the primary-matrix operator => improved multiple prediction
  - the data-matrix operator
  - blended wavefields
- Outlook
  - wavefield predictions with improved spectral and amplitude properties
  - wavefield predictions from blended data
  - sparsity-promoting migration & full waveform inversion

Acknowledgments

The authors of CurveLab (Demanet, Ying, Candes, Donoho)

Dr. Verschuur for his synthetic data and the estimates for the primaries.

The SLIM team Sean Ross Ross, Cody Brown and Henryk Modzeleweski for developing SLIMPy: operator overloading in python

These results were created with Madagascar and SPARCO.

This work was in part financially supported by the Natural Sciences and Engineering Research Council of Canada Discovery Grant (22R81254) and the Collaborative Research and Development Grant DNOISE (334810-05) of F.J.H. This research was carried out as part of the SINBAD project with support, secured through ITF (the Industry Technology Facilitator), from the following organizations: BG Group, BP, Chevron, ExxonMobil and Shell.

Further reading

1. E. van den Berg, M. P. Friedlander, G. Hennenfent, F. J. Herrmann, R. Saab, O. Yılmaz. Sparco: a testing framework for sparse reconstruction. To appear in ACM Trans. on Math. Soft. 2008.
2. G. Hennenfent, E. van den Berg, M. P. Friedlander, and F. J. Herrmann. New insights into one-norm solvers from the Pareto curve. Geophysics, Vol. 73, No. 4, 2008.
3. Herrmann, F. J., Wang, D., Hennenfent, G. and Moghaddam, P. Curvelet-based seismic data processing: a multiscale and nonlinear approach. Geophysics, Vol. 73, No. 1, pp. A1–A5, 2008.
4. Lin, T. and Herrmann, F. J., Compressed wavefield extrapolation. Geophysics, vol. 72, 5, SM77-SM93, 2007.
5. Tim T.Y. Lin, Evgeniy Lebed, Yogi A. Erlangga and F. J. Herrmann. Interpolating solutions of the Helmholtz equation with compressed sensing. In the proceedings of the Society of Exploration Geophysicists International Exposition and Annual Meeting (SEG), Las Vegas, 2008.
6. Yogi A. Erlangga and F. J. Herrmann. An iterative multilevel method for computing wavefields in frequency-domain seismic inversion. In the proceedings of the Society of Exploration
7. Herrmann, F. J., Wang, D. and Gilles Hennenfent., G. Multiple prediction from incomplete data with the focused curvelet transform. In the proceedings of the Society of Exploration
8. Herrmann, F. J., Wang, D. and Gilles Hennenfent., G. Multiple prediction from incomplete data with the focused curvelet transform. In the proceedings of the Society of Exploration
9. Felix J. Herrmann, Yogi A. Erlangga, Tim T.Y. Lin. Compressive simultaneous full-waveform simulation. Technical Report TR-2008-09. [This is a revision to TR-2008-03]

slim.eos.ubc.ca