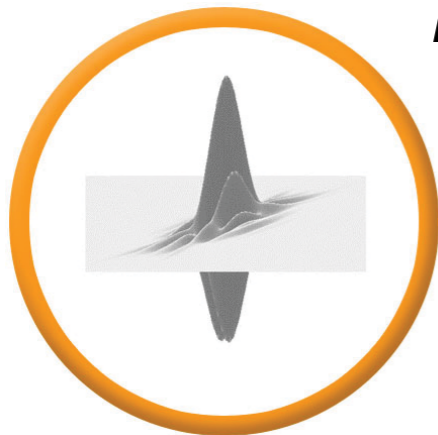




Randomized wavefield inversion



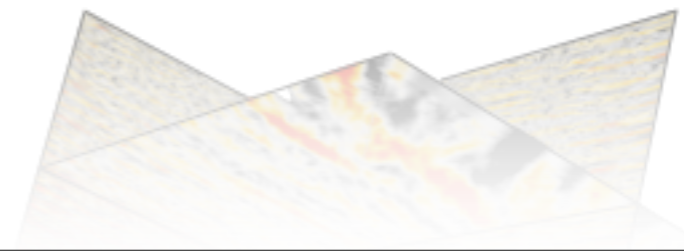
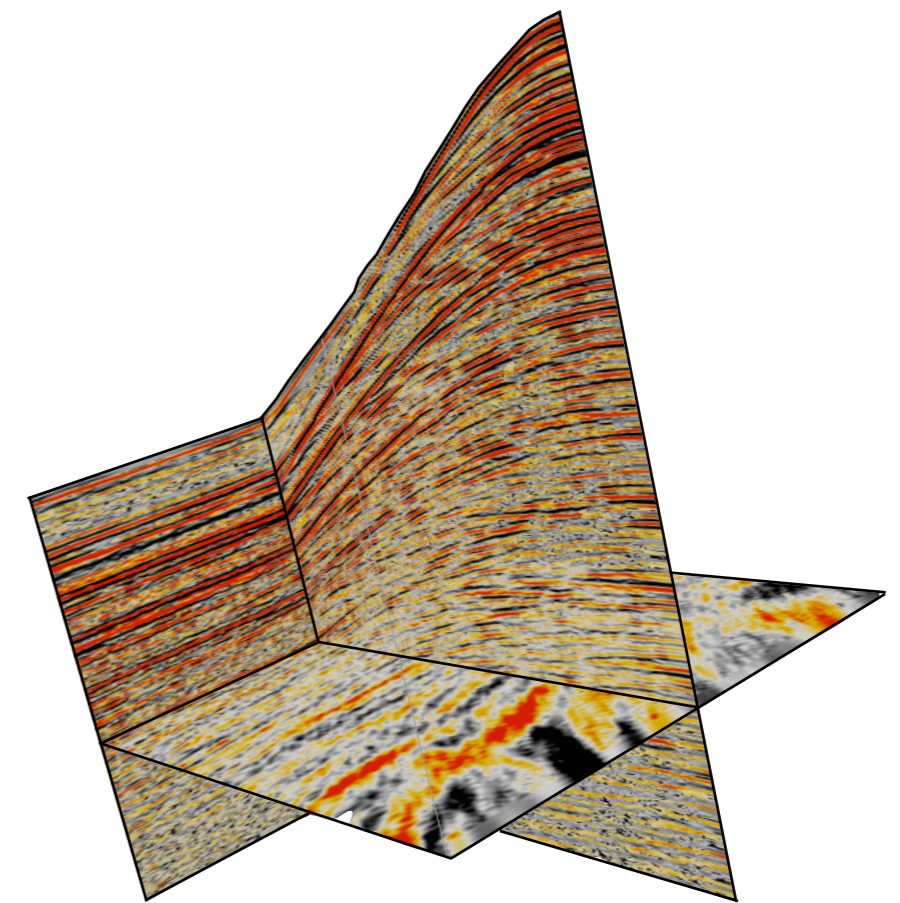
Felix J. Herrmann*

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Joint work with Yogi Erlangga, and Tim Lin

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Motivation

- **Seismic data processing, modeling & inversion:**

- firmly rooted in Nyquist's sampling paradigm for (modeled) wavefields
- too *pessimistic* for signals with *structure*
- existence of sparsifying transforms (e.g. curvelets)

- **Major impediment: “*curse of dimensionality*”**

- *acquisition* >> *processing & inversion* >> *modeling* **costs** are proportional to the **size** of *data* and *image* space

- **Solution strategy:**

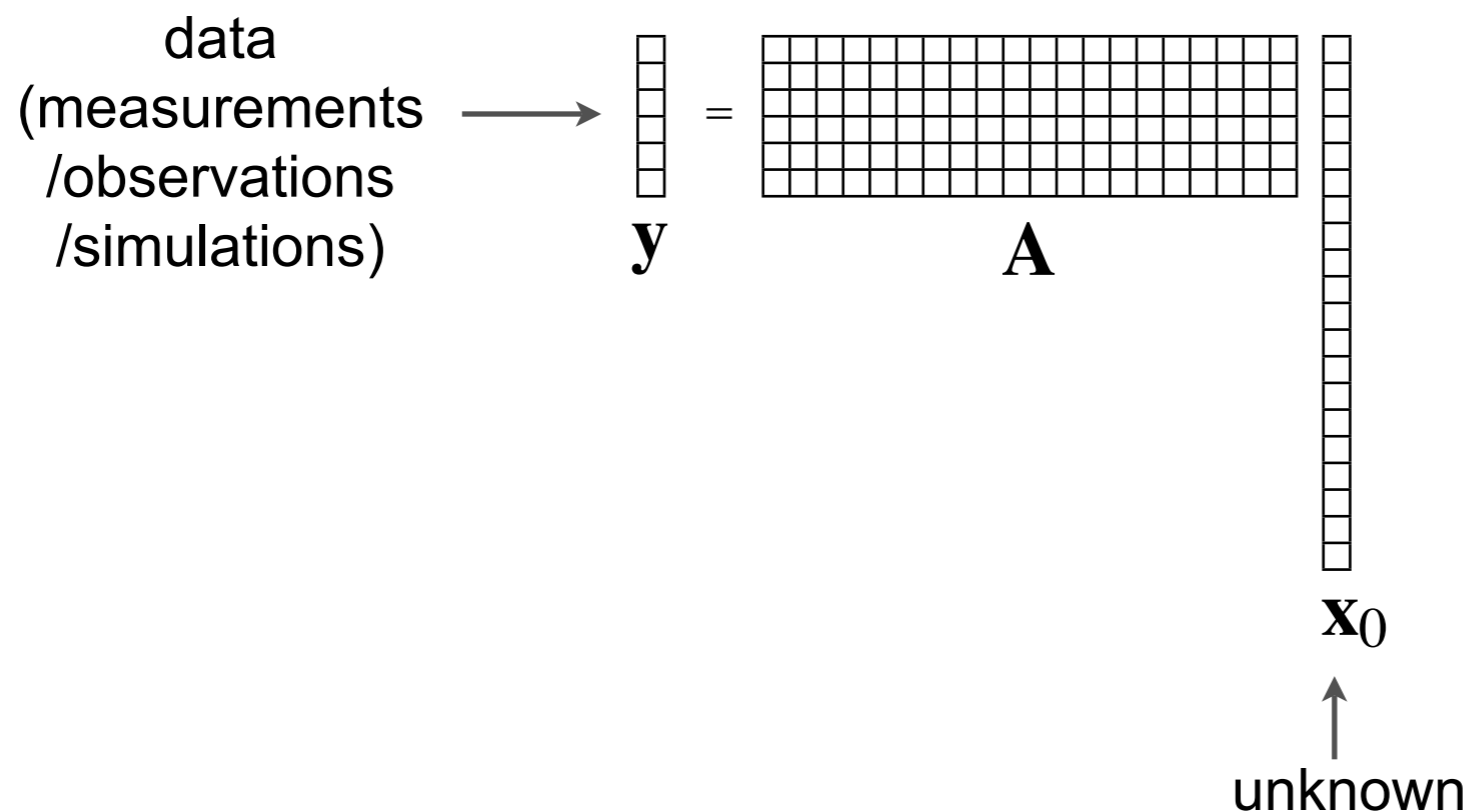
- *leverage new* paradigm of *compressive sensing* (CS)
 - identify simultaneous acquisition as CS
 - reduce acquisition, simulation, and inversion costs by ***randomization*** and deliberate ***subsampling***
- recovery from sample **rates** \approx **computational cost** *proportional* to **transform-domain sparsity** of *data* or *model*

Today's agenda

- Brief introduction to *compressive sensing*
 - *sparsifying* transforms
 - *randomized* = *incoherent* downsampling
 - *nonlinear* recovery by *sparsity* promotion
- *Sparsity-promoting recovery* from ***randomized simultaneous measurements***
 - missing *separated* shots versus missing *simultaneous* shots
 - recovery from simultaneous data *with* and *without* primary prediction (CSed EPSI)
- *Joint sparsity-promoting recovery* from ***randomized image volumes***
 - leverage *focusing*
 - *reduction* of model-space wavefields

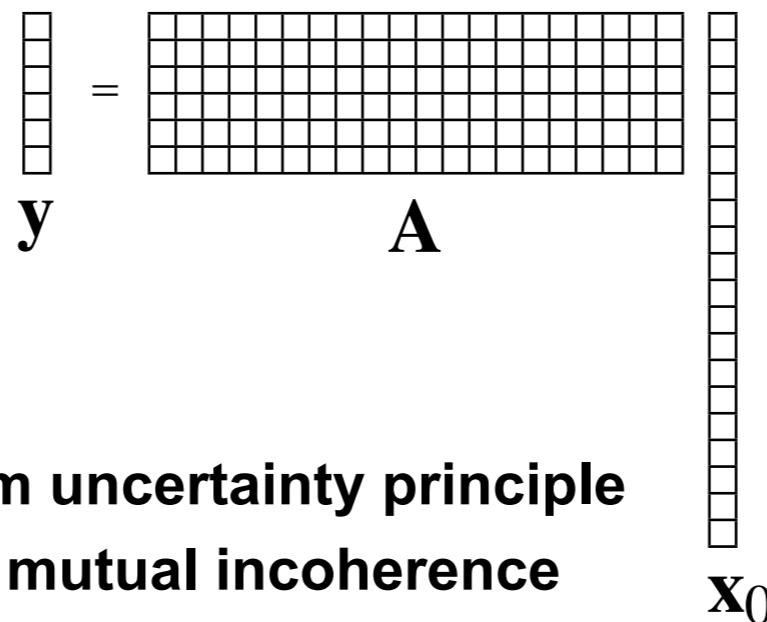
Problem statement

Consider the following (severely) underdetermined system of linear equations



Is it possible to recover \mathbf{x}_0 accurately from \mathbf{y} ?

Perfect recovery



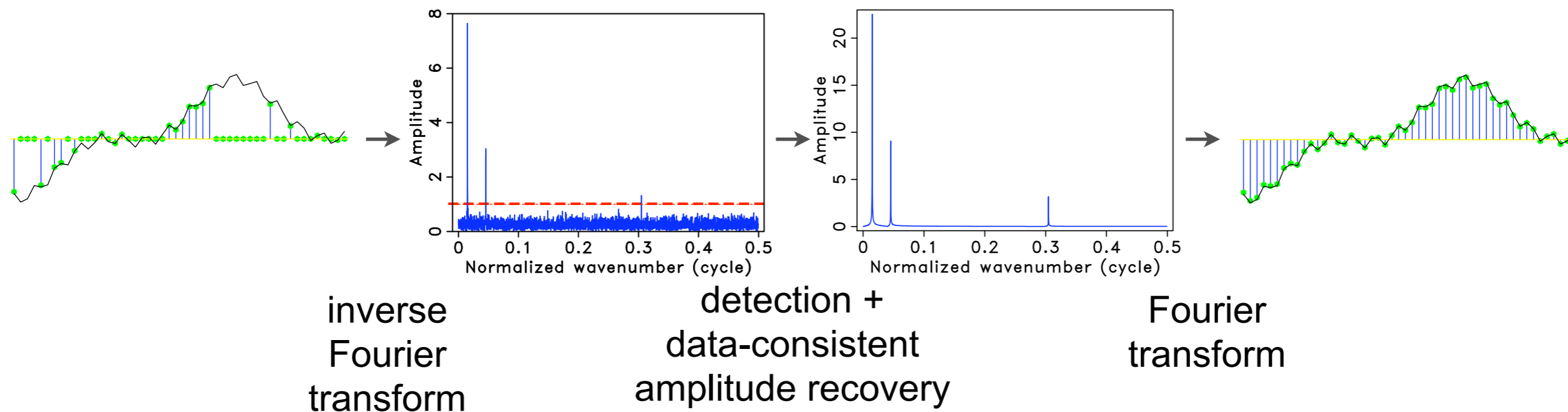
- conditions
 - A obeys the **uniform uncertainty principle**
 - **randomized A \Leftrightarrow mutual incoherence**
 - x_0 is **sufficiently sparse**

- **nonlinear** recovery procedure:

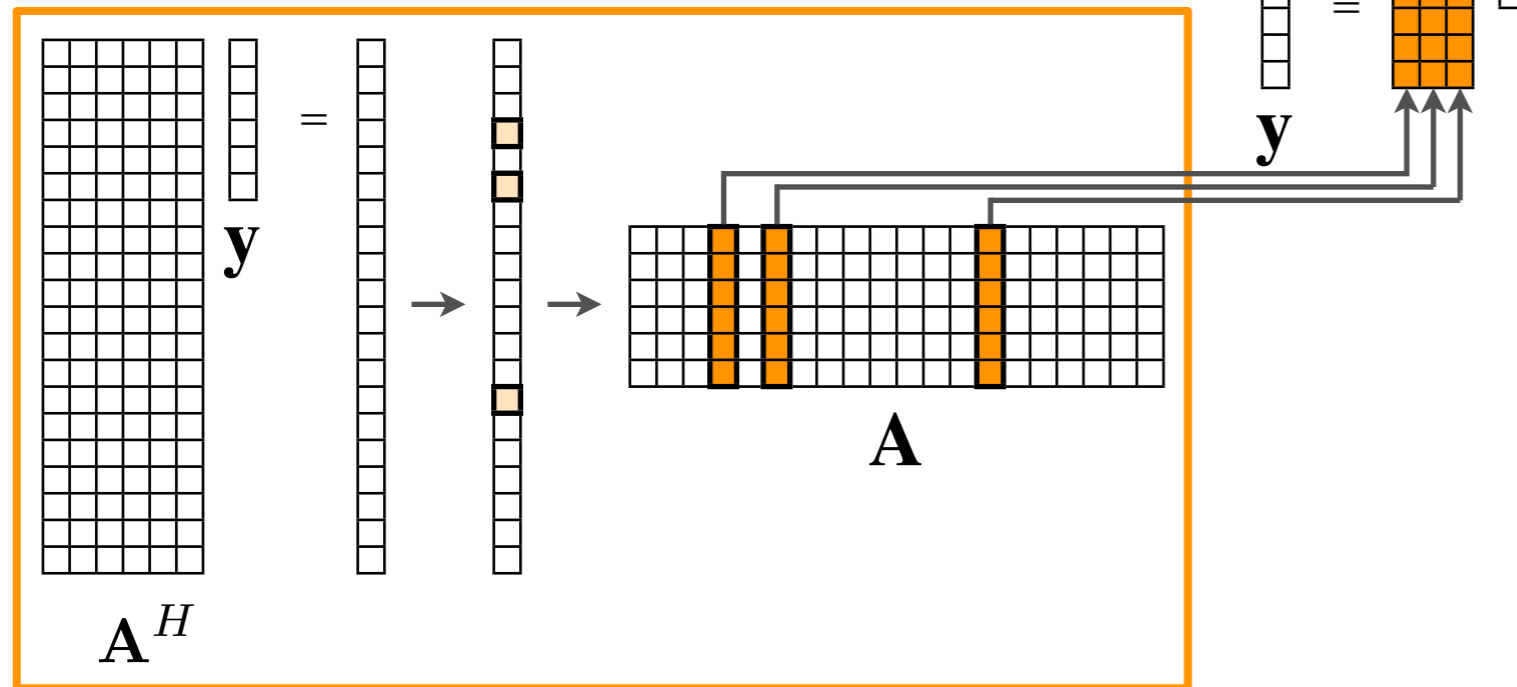
$$\underbrace{\min_{\mathbf{x}} \|\mathbf{x}\|_1}_{\text{sparsity}} \quad \text{s.t.} \quad \underbrace{\mathbf{Ax} = \mathbf{y}}_{\text{perfect reconstruction}}$$

- performance
 - **S -sparse vectors recovered from roughly on the order of S measurements** (to within constant and \log factors)

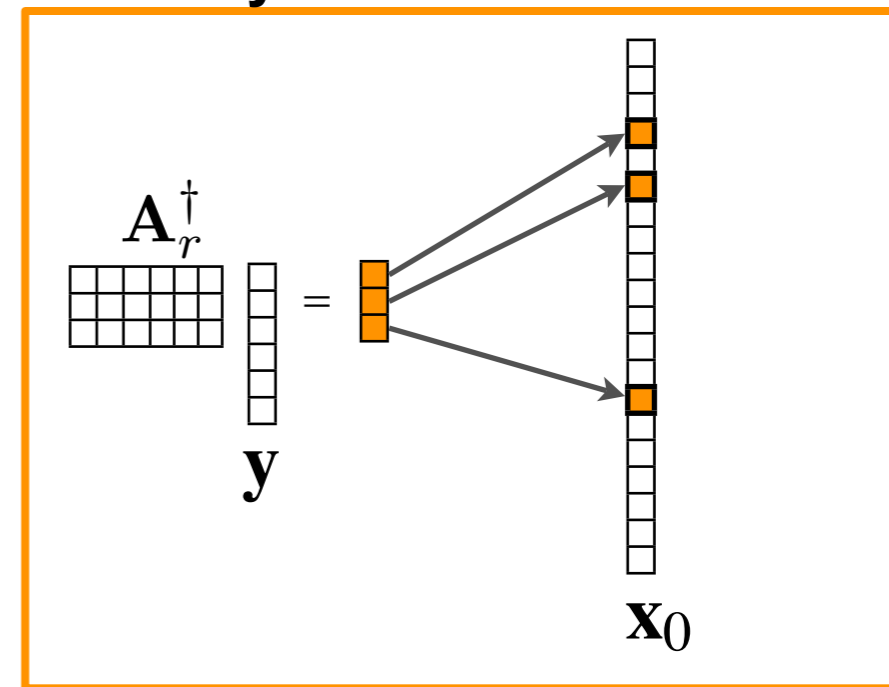
NAIVE sparsity-promoting recovery



detection



data-consistent amplitude recovery



Extensions

- Use CS principles to select *physically* appropriate
 - *measurement* basis \mathbf{M} = *random* phase encoder
 - *randomized* restriction matrix \mathbf{R} = downsampler
 - sparsifying transform \mathbf{S} (e.g. curvelets)
 - driven by signal type, physics, and type of acquisition (e.g. fMRI vs seismic)
- Sparse signal representation:

$$\mathbf{y} = \mathbf{A}\mathbf{x}_0$$

with

$$\mathbf{A} = \mathbf{R}\mathbf{M}\mathbf{S}^H$$

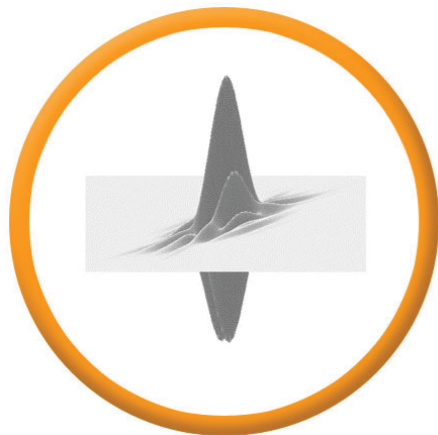
restriction
matrix

measurement
matrix

sparsity
matrix

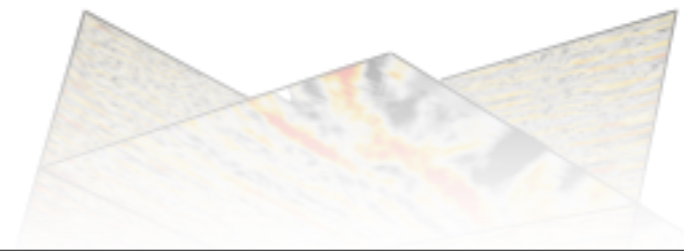
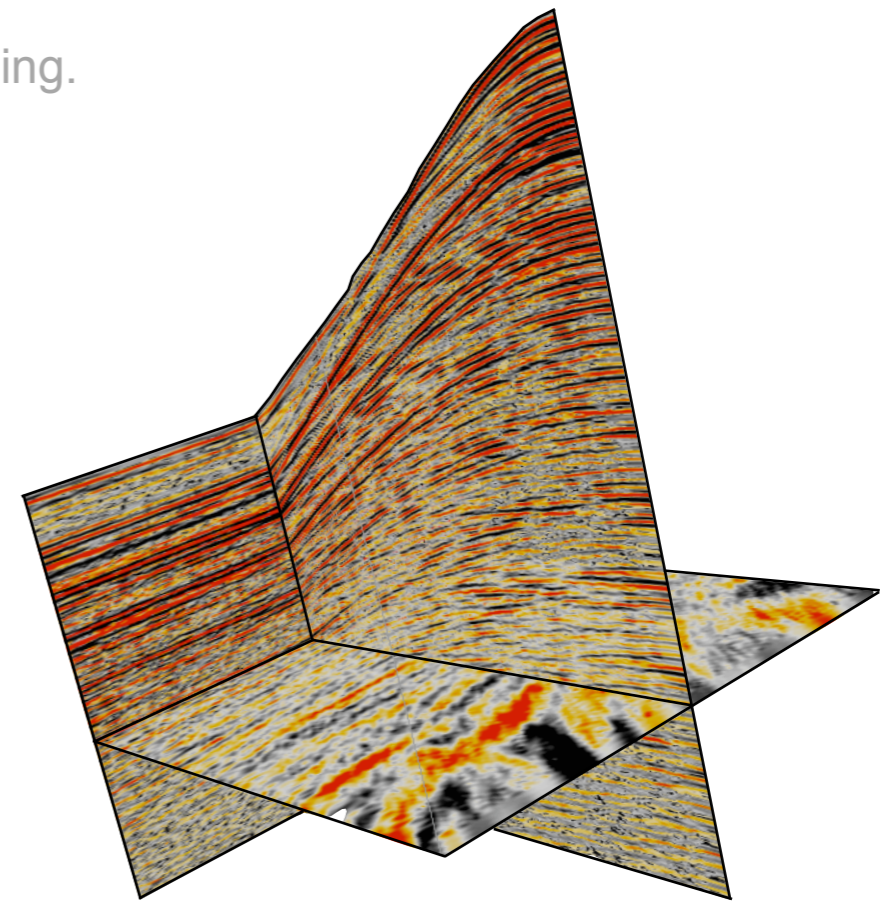
Selection is aimed at turning *aliases/coherent subsampling artifacts* into harmless **noise** ...

Recovery from *randomized* simultaneous measurements



Tim T.Y. Lin and Felix J. Herrmann, Designing simultaneous acquisitions with compressive sensing. Submitted Abstract, Amsterdam, 2009, EAG

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Relation to existing work

- **Simultaneous & continuous acquisition:**

- *A new look at marine simultaneous sources* by C. Beasley, '08
- *Simultaneous Sourcing without Compromise* by R. Neelamani & C.E. Krohn, '08.
- *Changing the mindset in seismic data acquisition* by A. Berkout, '08
- *Independent simultaneous sweeping - A method to increase the productivity of land seismic crews* by D. Howe, M. Foster, T. Allen, B. Taylor, and I. Jack, '08

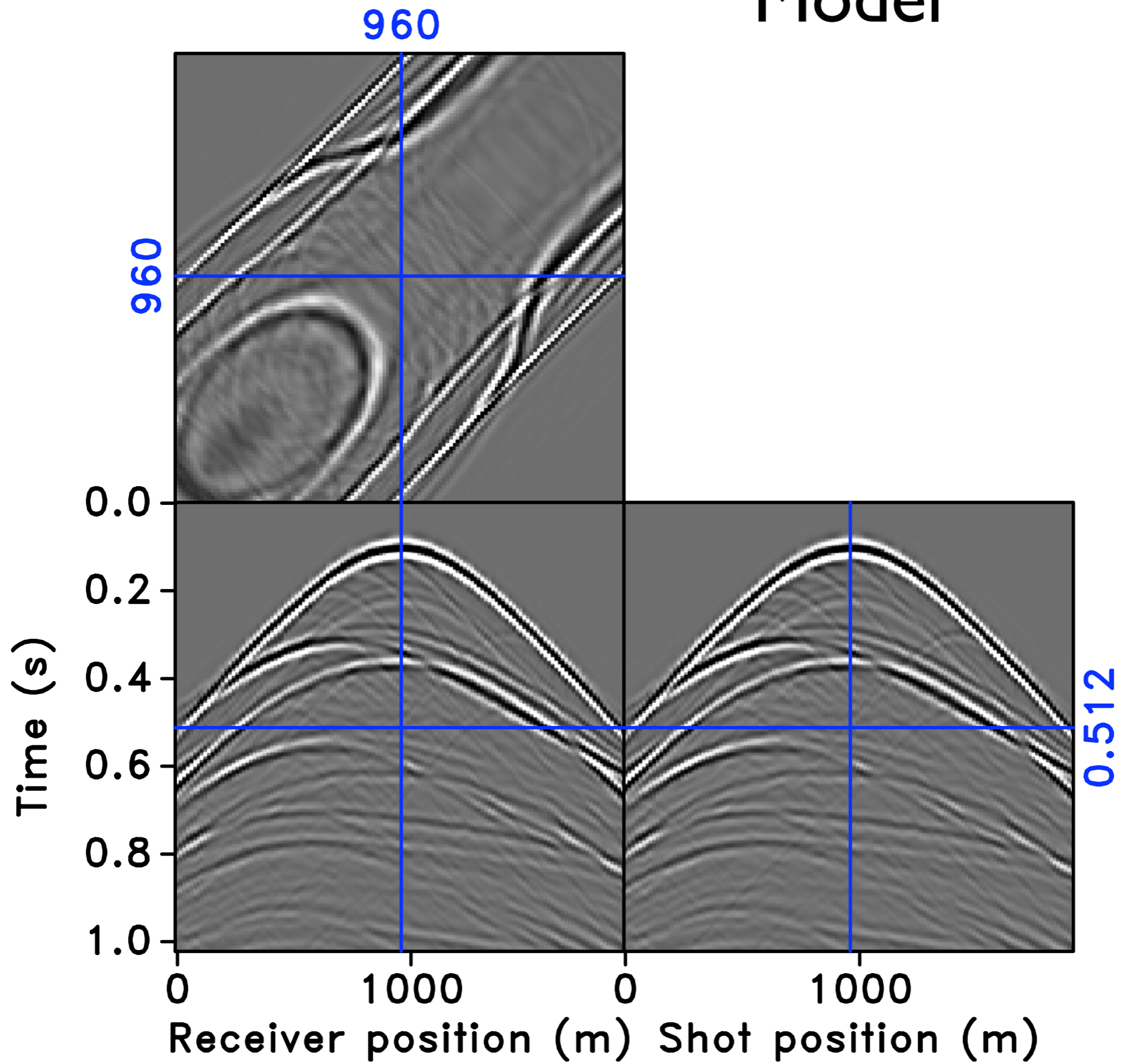
- **Primary prediction through wavefield inversion:**

- *Elimination of free-surface related multiples without need of the source wavelet* by L. Amundsen, '01
- *Primary estimation by sparse inversion and its application to near offset reconstruction* by G. van Groenenstijn and D. Verschuur, '09

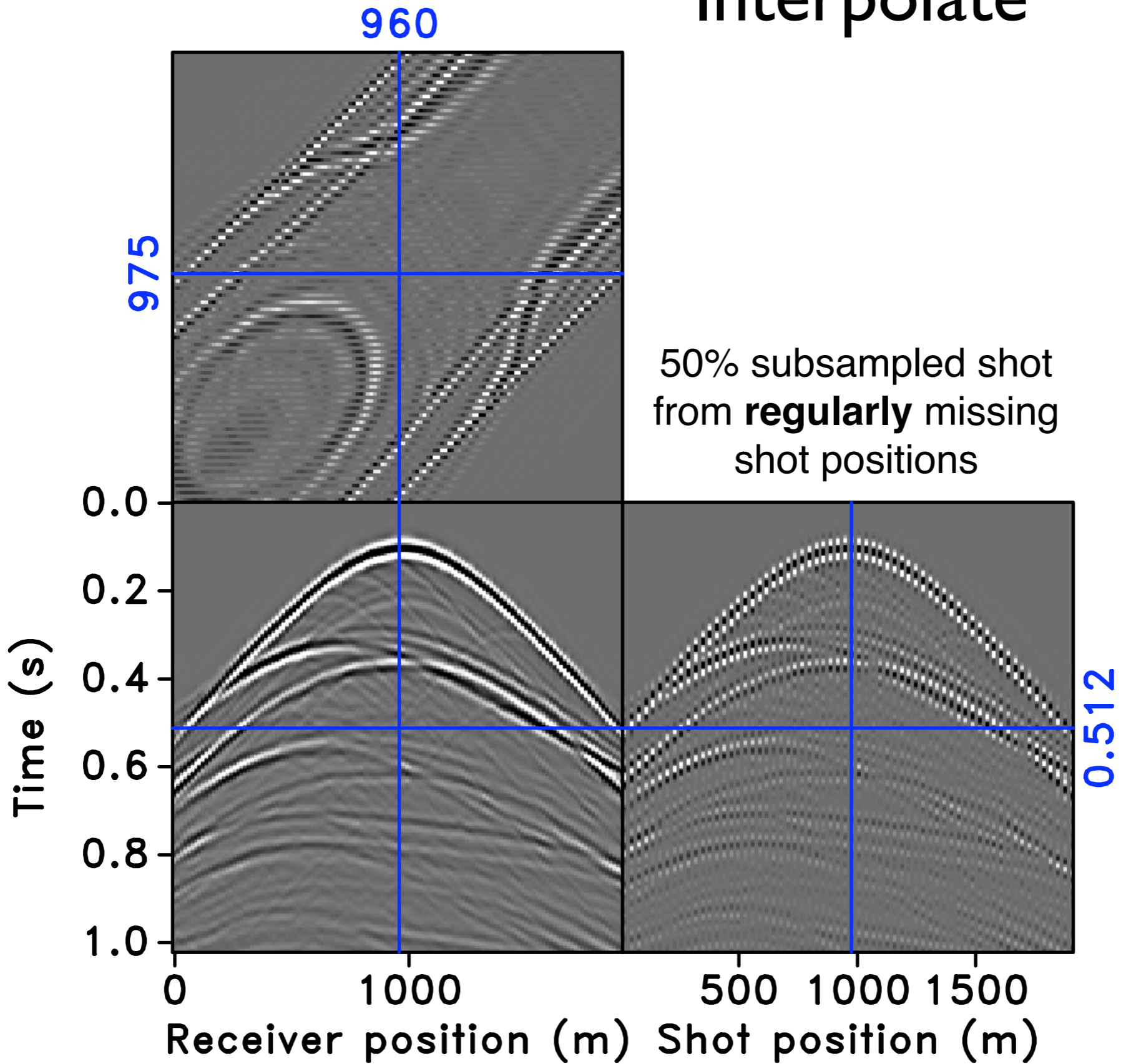
Two questions

- **Question I: What is better? Having missing *single-source* or *missing randomized simultaneous* experiments?**
- Comparison between different undersampling strategies for source experiments:
 - ***Deterministic*** missing shot positions
 - ***Randomized*** jittered shot positions
 - ***Randomized*** simultaneous shots
- **Question II: What is better? First recover and then process or process directly in the compressed domain?**
- Example: ***randomized*** primary prediction with EPSI

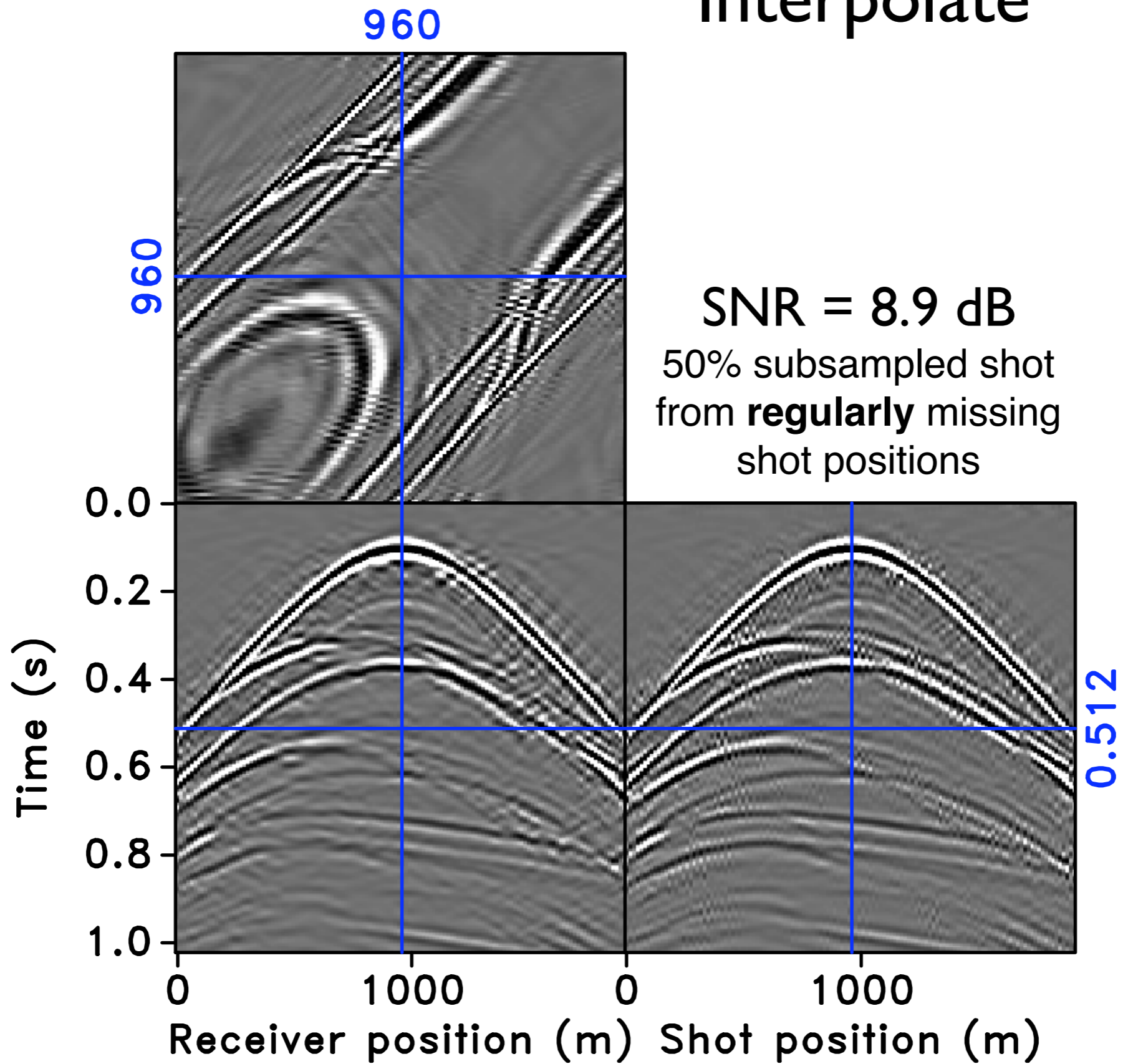
Model



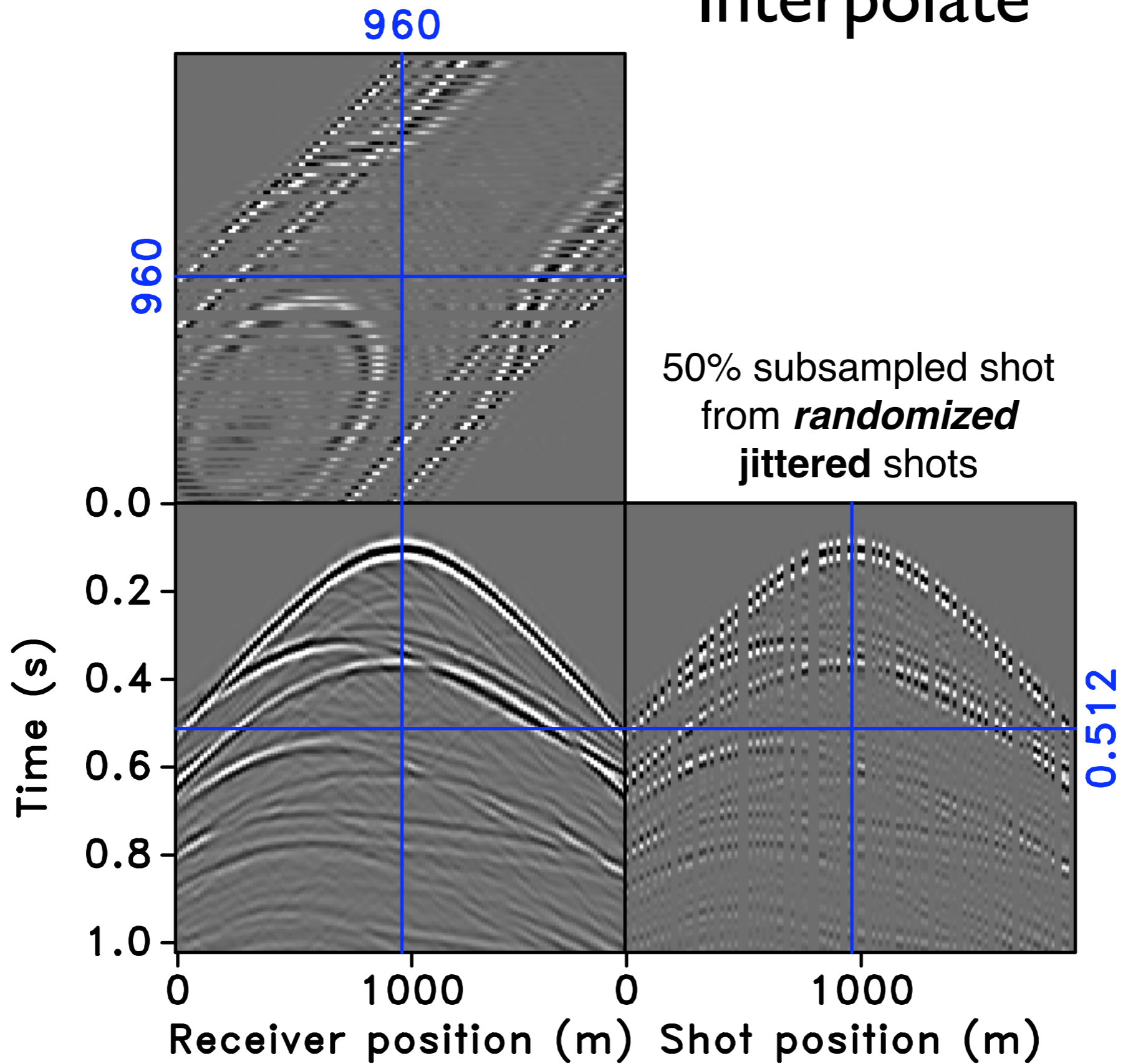
Interpolate



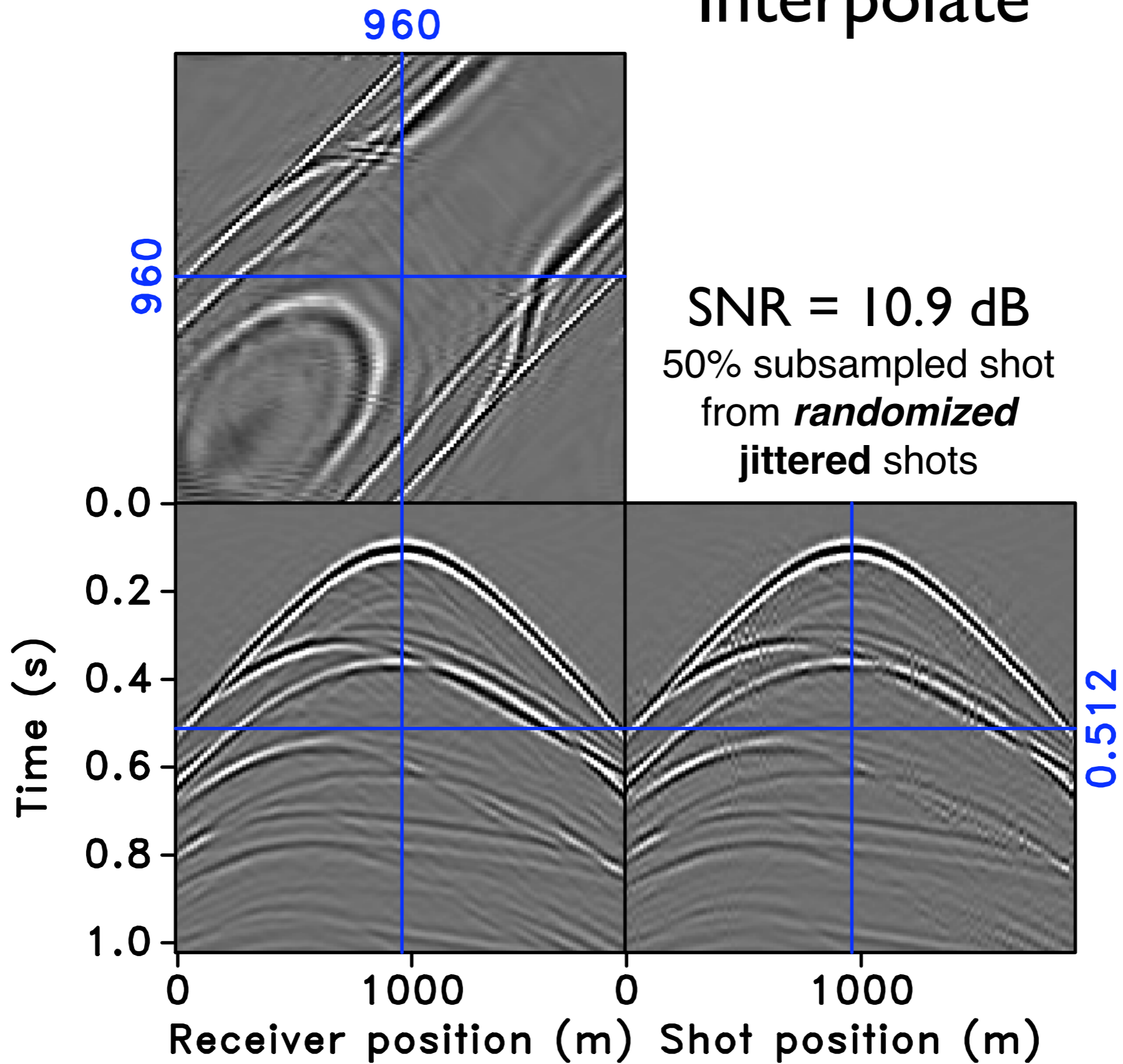
Interpolate



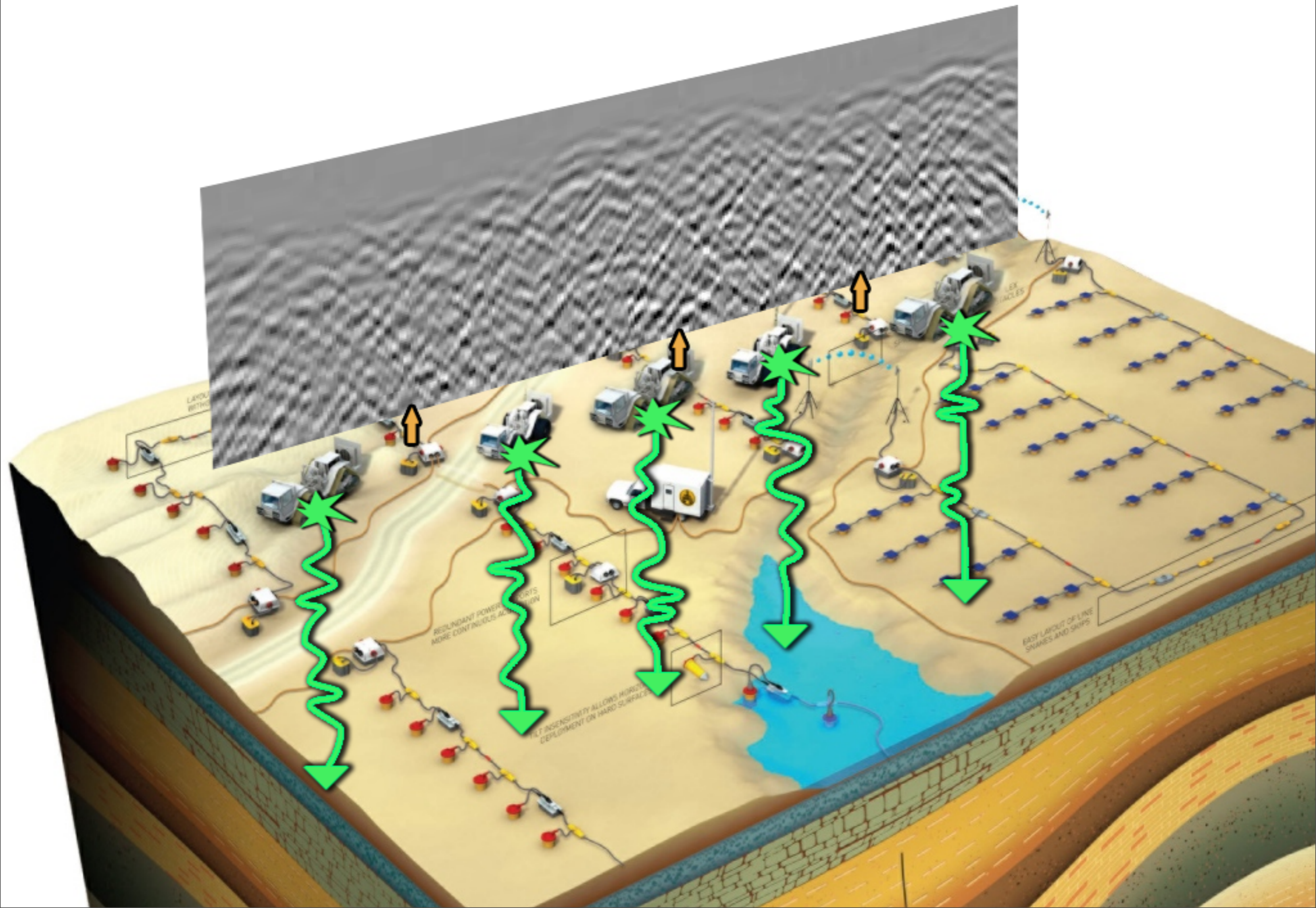
Interpolate



Interpolate

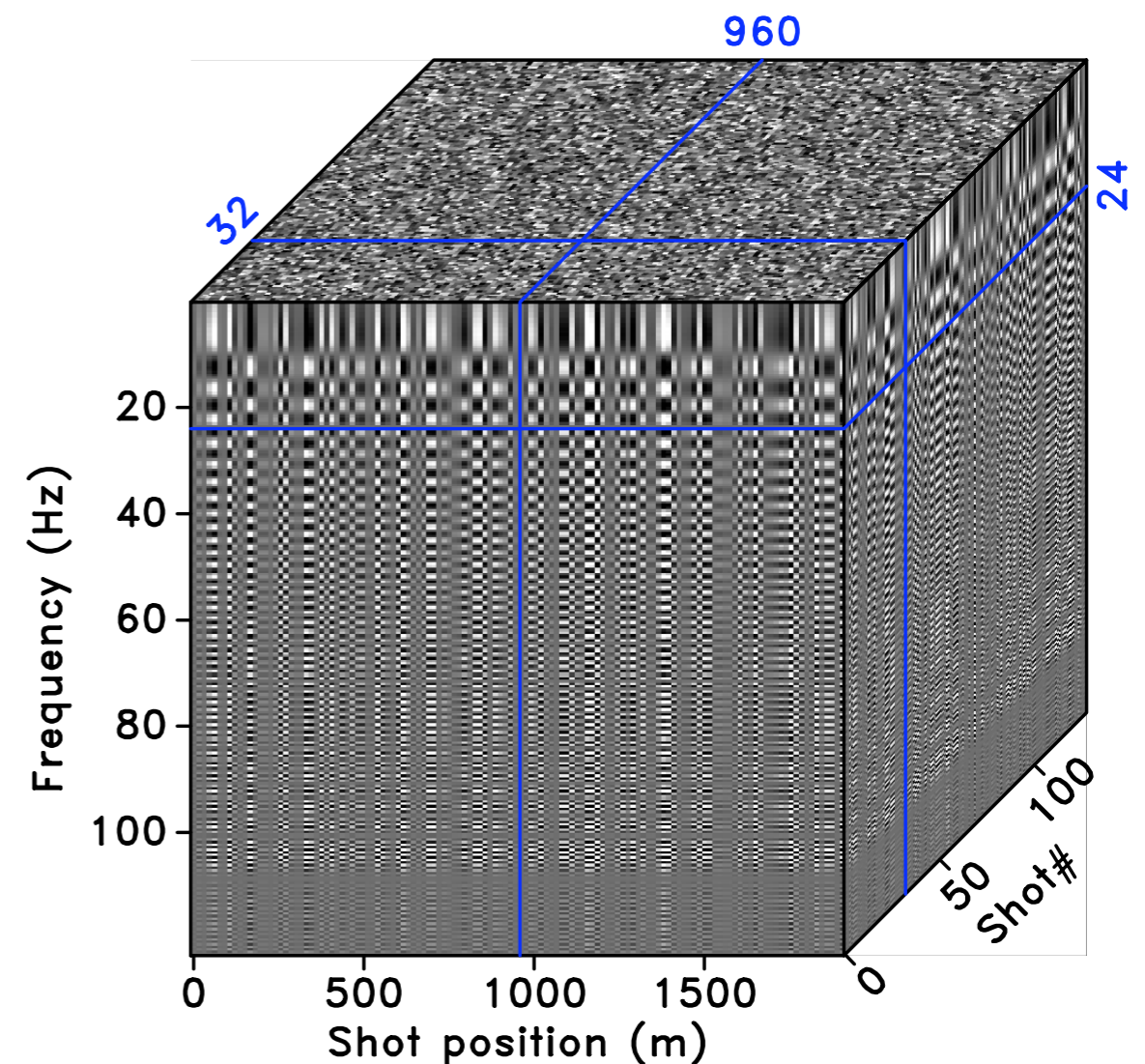
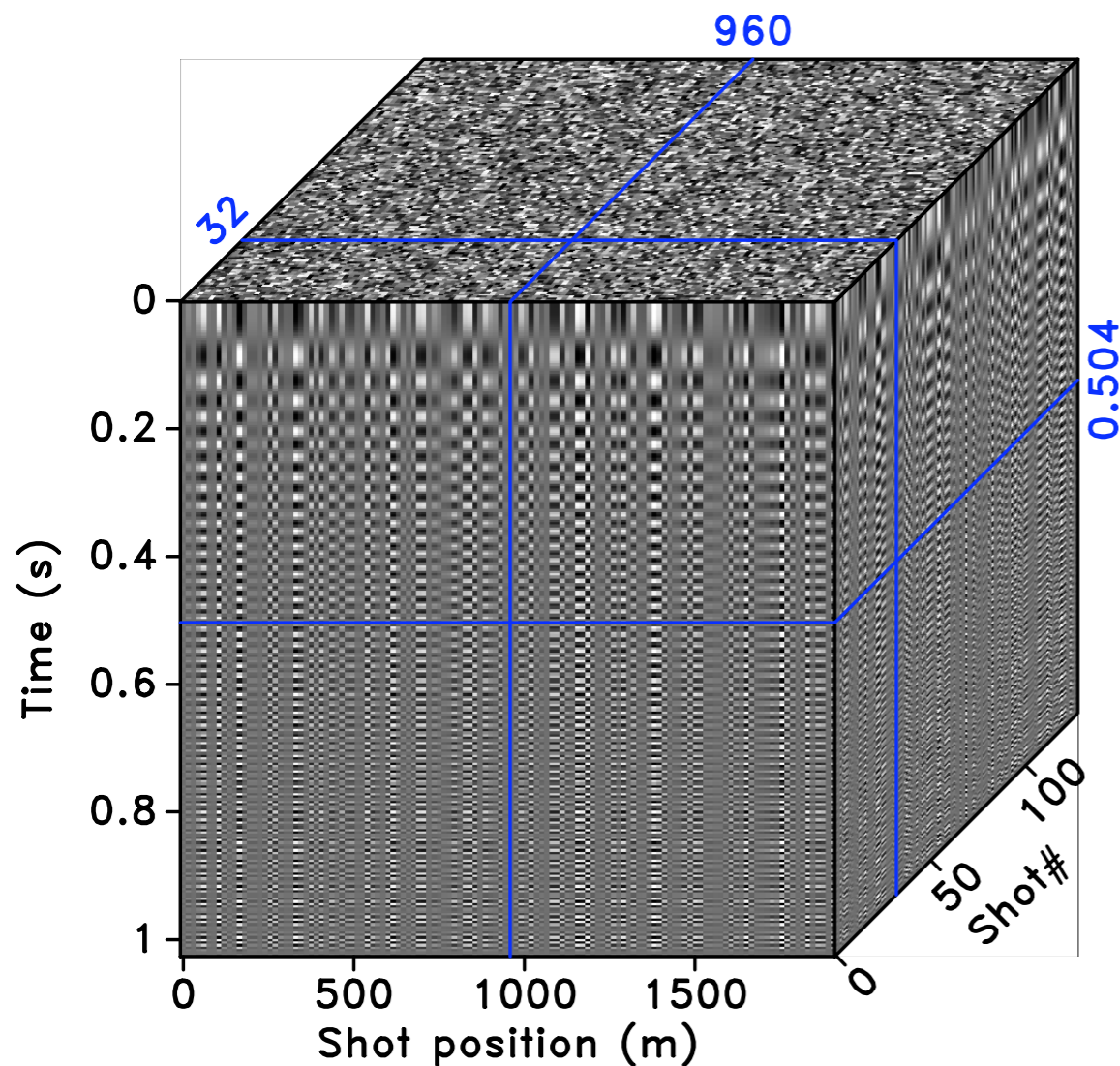


Simultaneous & continuous sources

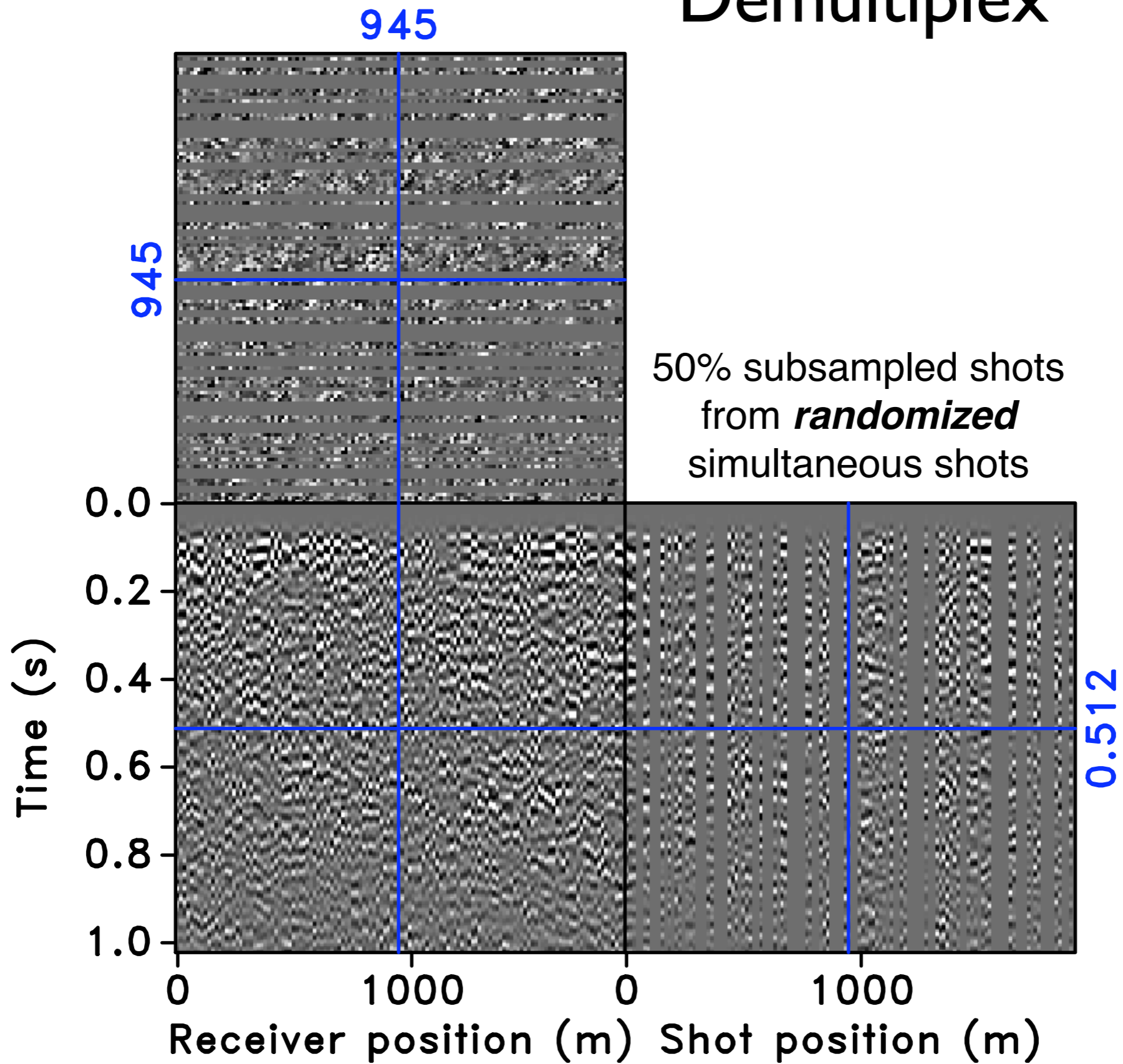


Randomized simultaneous sweep signals

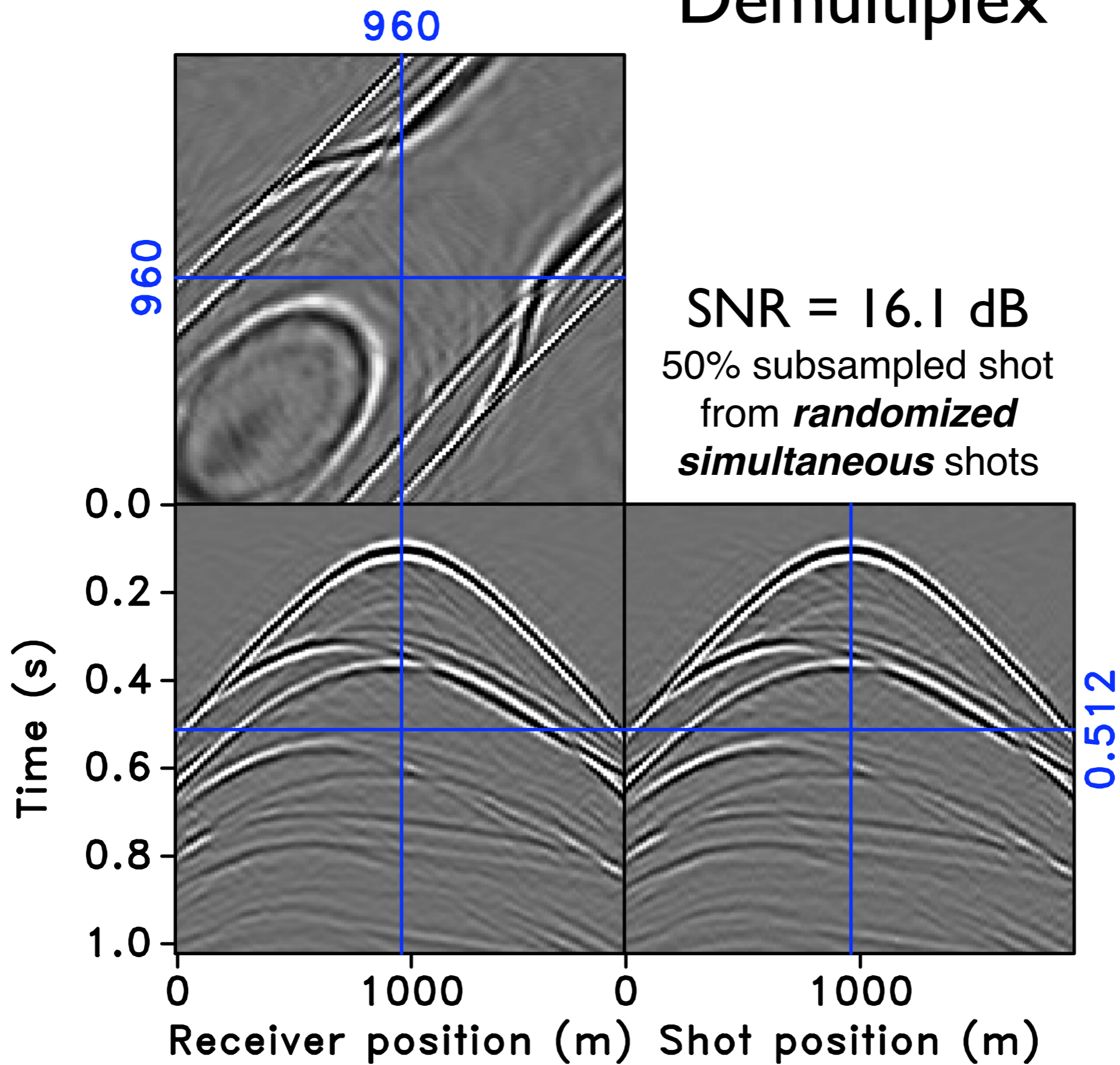
- Linearly ramping seismic sweep, 5 to 110 Hz
- Simultaneous source at all positions, each randomly phase encoded

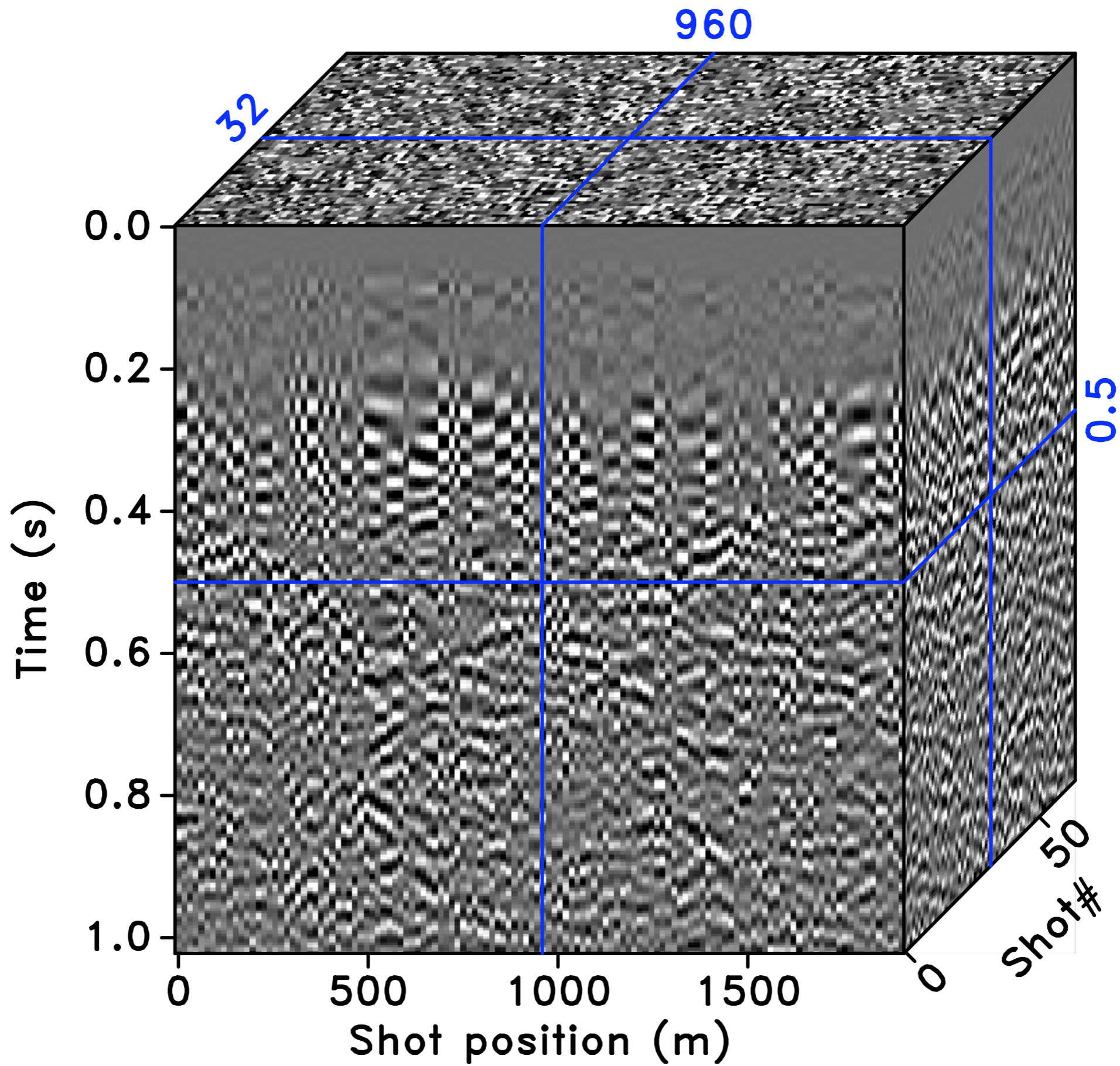


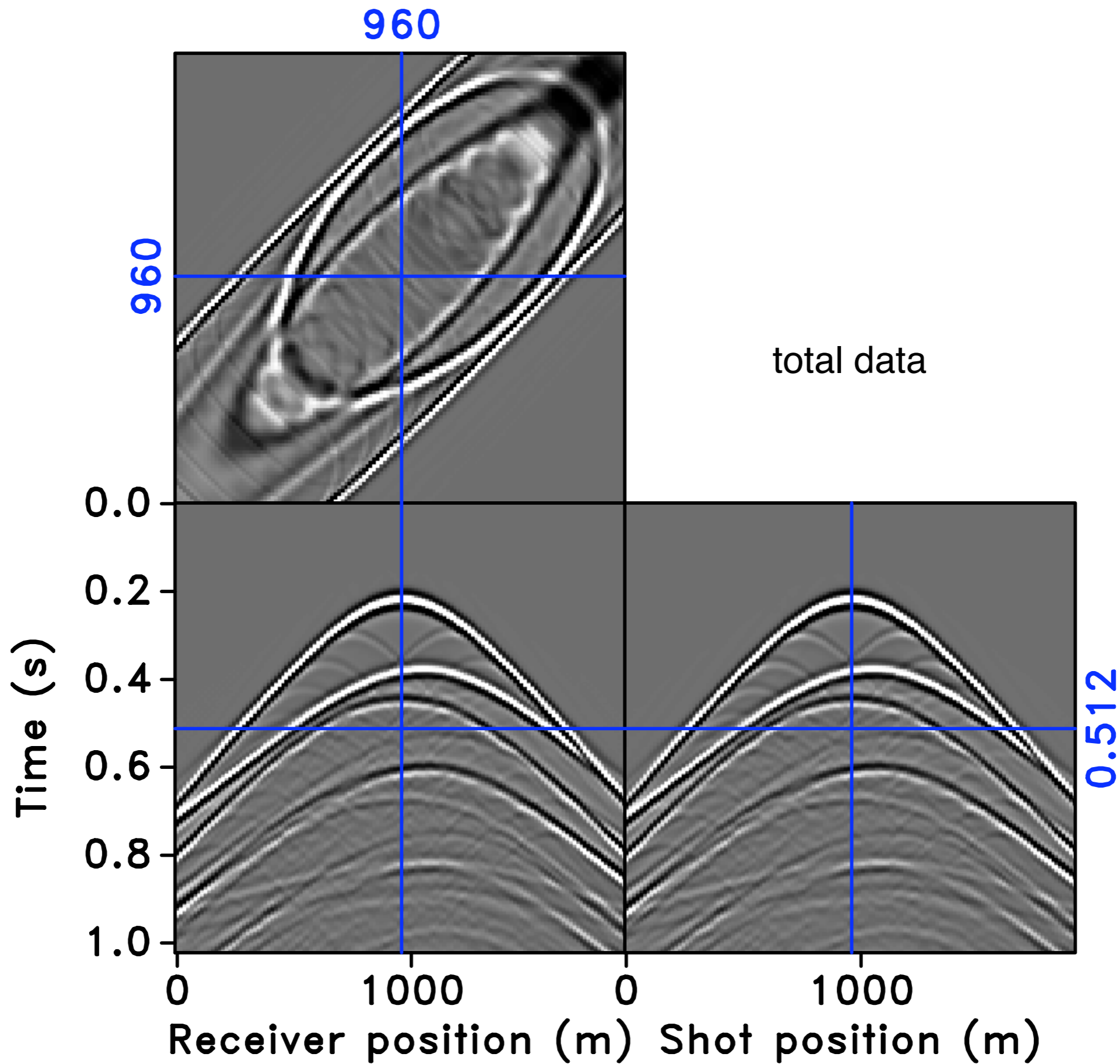
Demultiplex

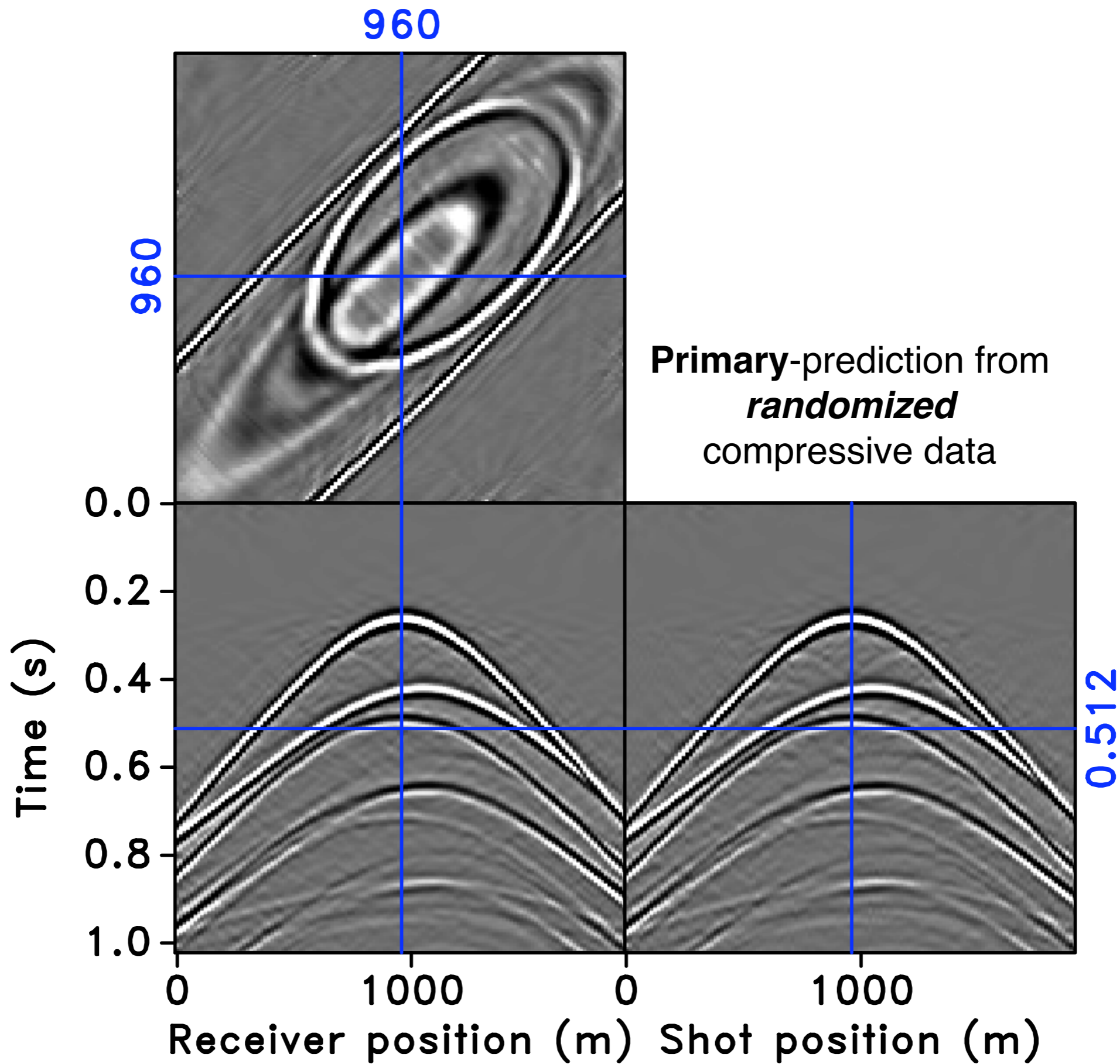


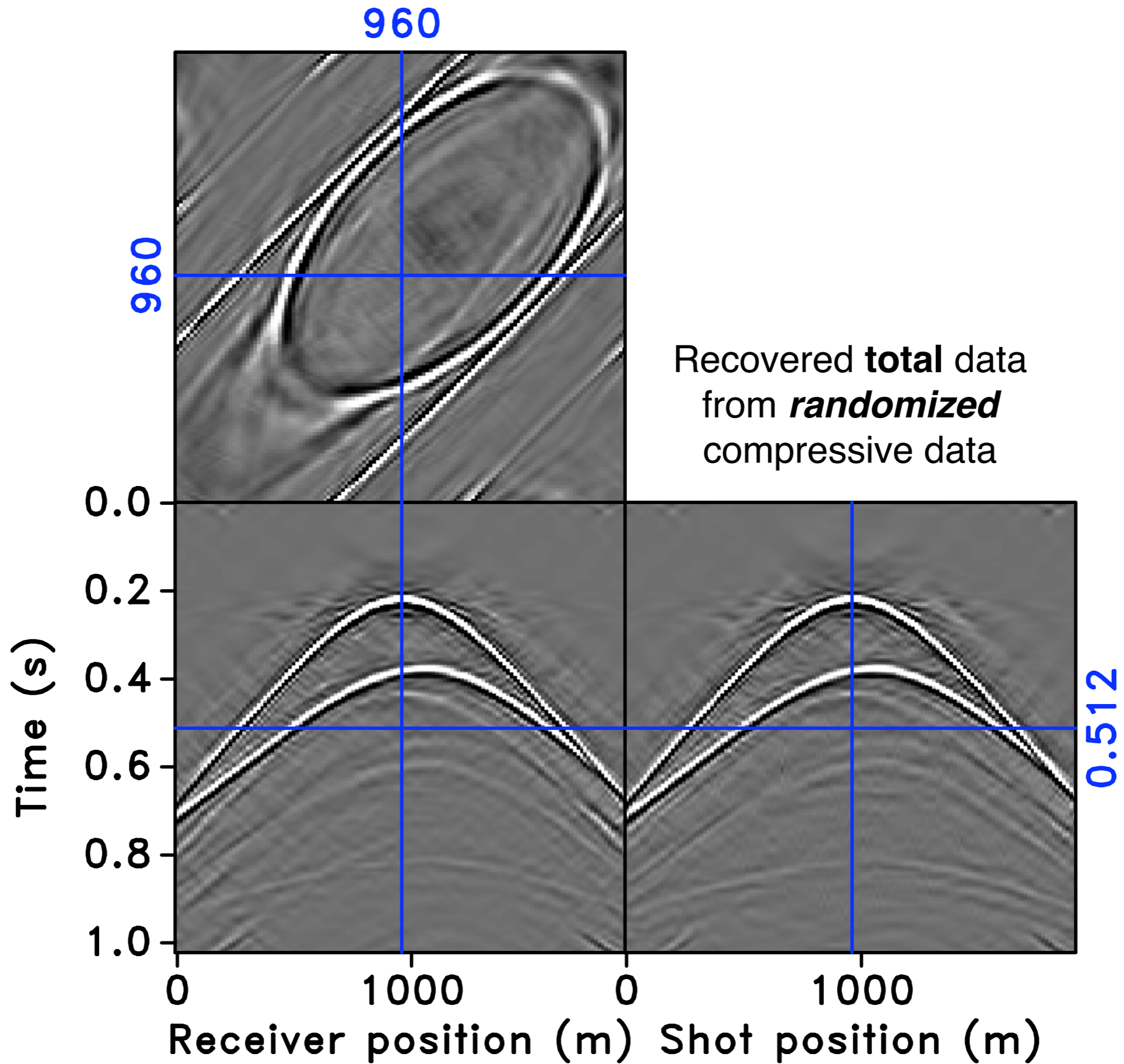
Demultiplex

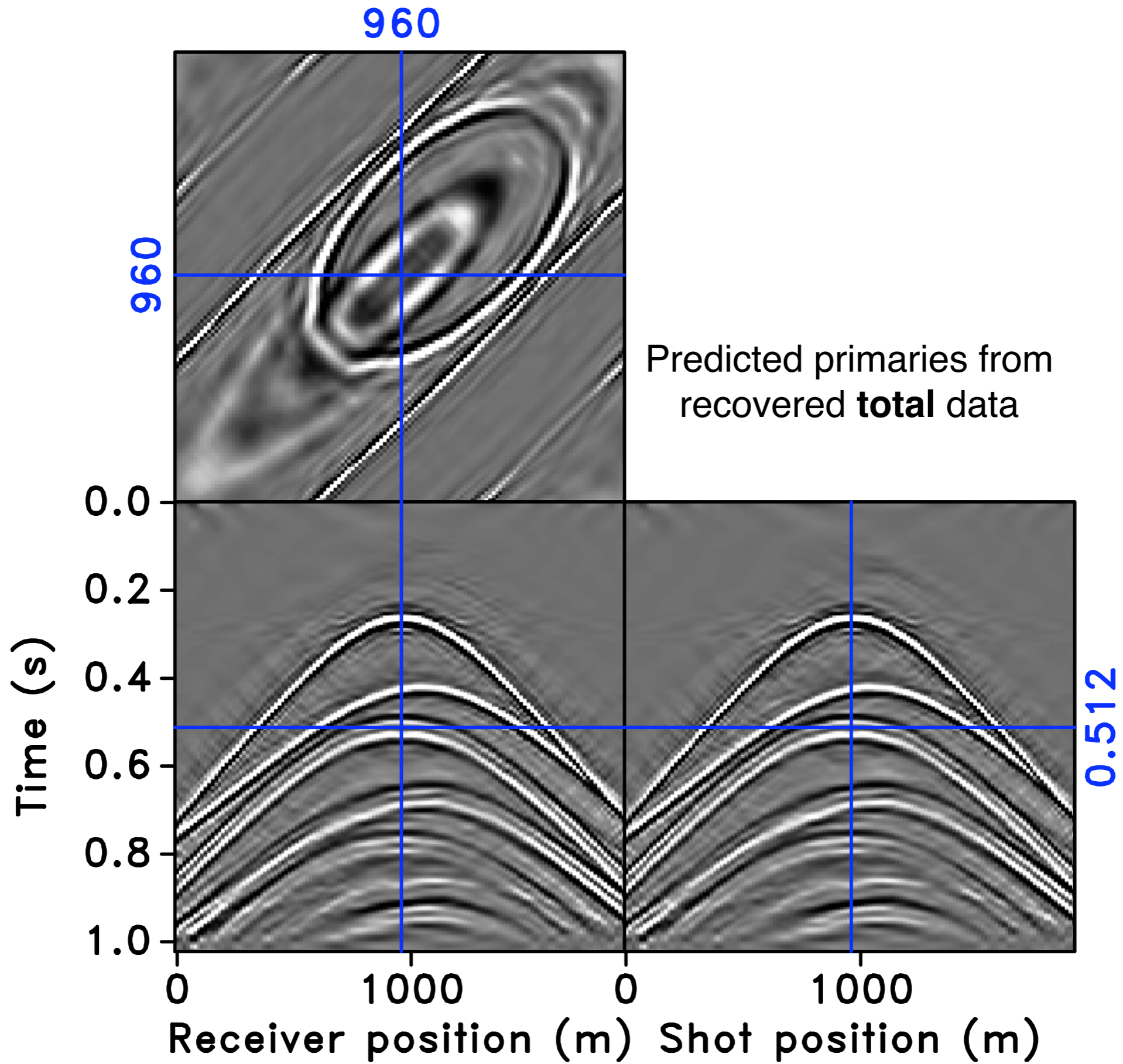












Observations

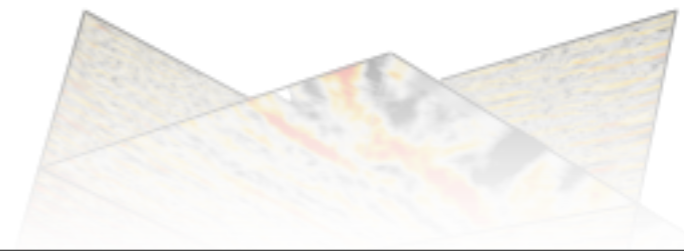
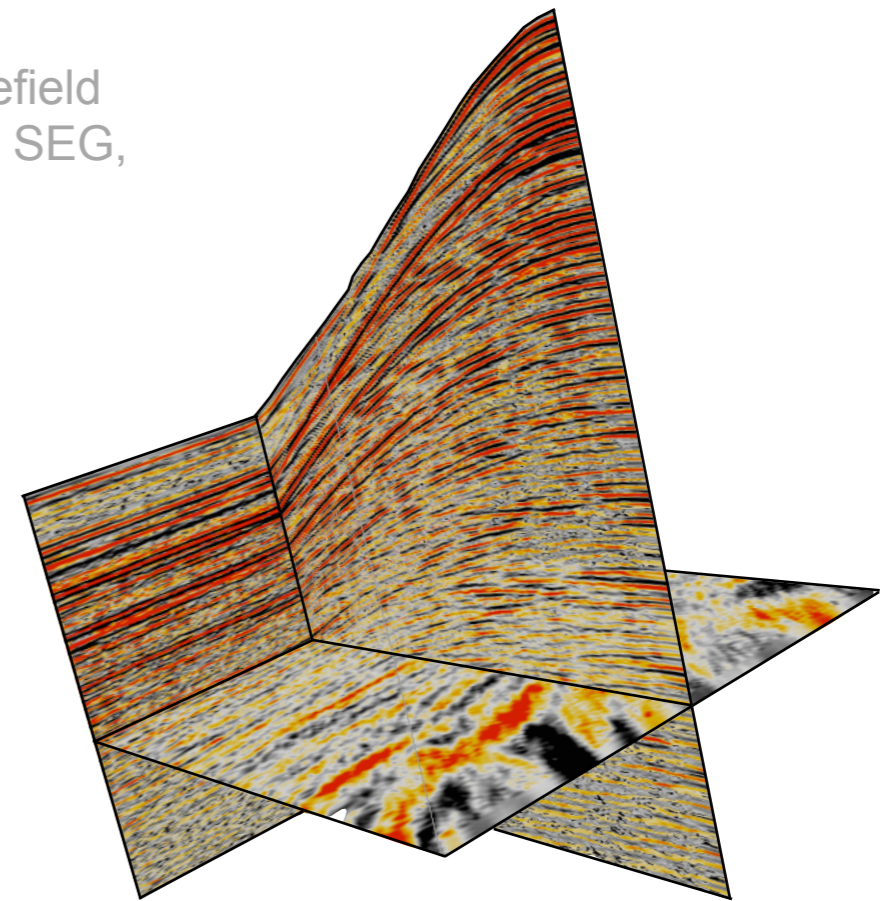
- **Incoherent *randomized*** sampling *crucial* for creating *favorable* recovery conditions for ***sparsity-promoting recovery*** from “**incomplete**” data
 - depends on the choice of ***downsampled randomization RM***
 - simultaneous acquisition is better for reconstruction
- Recovery greatly improves when **estimating primaries**
 - *deconvolved primaries* are **sparser** than **multiples**
 - **multiples** are mapped to **primaries**
 - example of ***randomized wavefield inversion*** with ***reduced sizes***
- Push recovery down into processing flow, i.e., compressive processing & imaging
- Extend these ideas to imaging = model-space compressive sampling

Recovery from *randomized* image volumes



Felix J. Herrmann, Compressive imaging by wavefield inversion with group sparsity. Submitted abstract, SEG, 2009, Houston. Technical Report TR-2009-01

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Strategy

- Leverage CS towards solutions of wave simulation & imaging problems
- Subsample solution deliberately, followed by CS recovery
- Speedup if recovery costs $<$ gain in reduced system size
 - computation
 - storage
- Examples:
 - compressed imaging by CS sampling in the model space

Relation to existing work

- **Simultaneous & continuous acquisition:**

- *Efficient Seismic Forward Modeling using Simultaneous Random Sources and Sparsity* by N. Neelamani and C. Krohn and J. Krebs and M. Deffenbaugh and J. Romberg, '08

- **Simultaneous simulations & migration:**

- *Faster shot-record depth migrations using phase encoding* by Morton & Ober, '98.
- *Phase encoding of shot records in prestack migration* by Romero et. al., '00.

- **Imaging:**

- *How to choose a subset of frequencies in frequency-domain finite-difference migration* by Mulder & Plessix, '04.
- *Efficient waveform inversion and imaging: A strategy for selecting temporal frequencies* by Sirque and Pratt, '04.

- **Full-waveform inversion:**

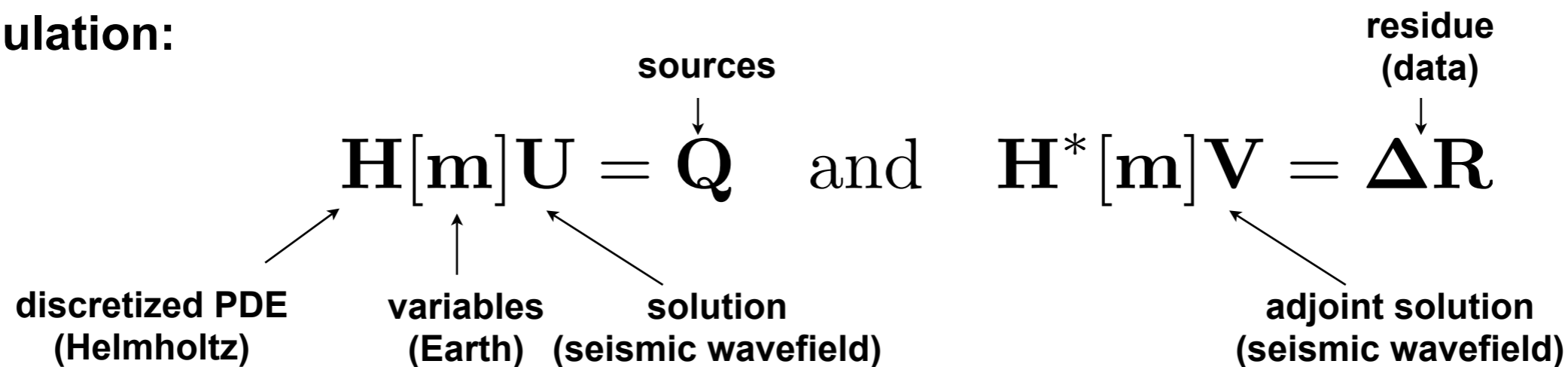
- *3D prestack plane-wave, full-waveform inversion* by Vigh and Starr, '08

- **Wavefield extrapolation:**

- *Compressed wavefield extrapolation* by T. Lin and F.J.H, '07
- *Compressive wave computations* by L. Demanet (SIA '08 MS79 & Preprint)

Essentials of seismic inversion

Simulation:

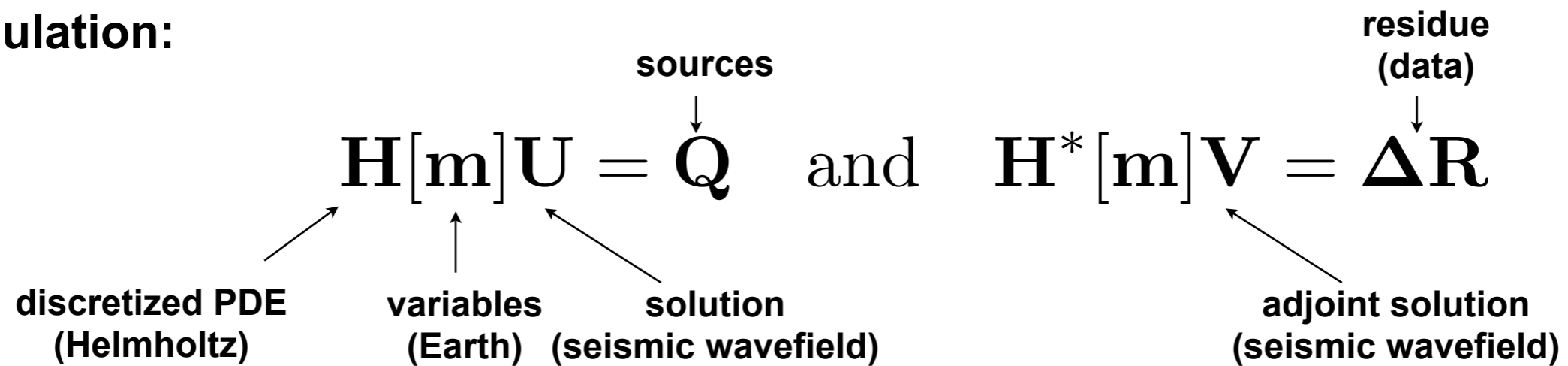


Imaging:

$$\begin{aligned} \text{image volume} \downarrow & \delta\hat{\mathbf{I}}(x_s, x_r, \omega) = (\mathbf{U} \circ \mathbf{V}^*) \\ \text{multi-D 'cross-correlation'} \downarrow & \\ \delta\mathbf{m}(x_s = x_r, t = 0) & = \sum_{\omega} \omega^2 \text{diag}\{\delta\hat{\mathbf{I}}\} \end{aligned}$$

Essentials of seismic inversion

Simulation:



- High-dimensional solutions are **extremely** expensive to compute
- Inversion (e.g. via Gauss-Newton) requires multiple solves
- Number of blocks in \mathbf{H} and number of **rhs** determine simulation & acquisition costs

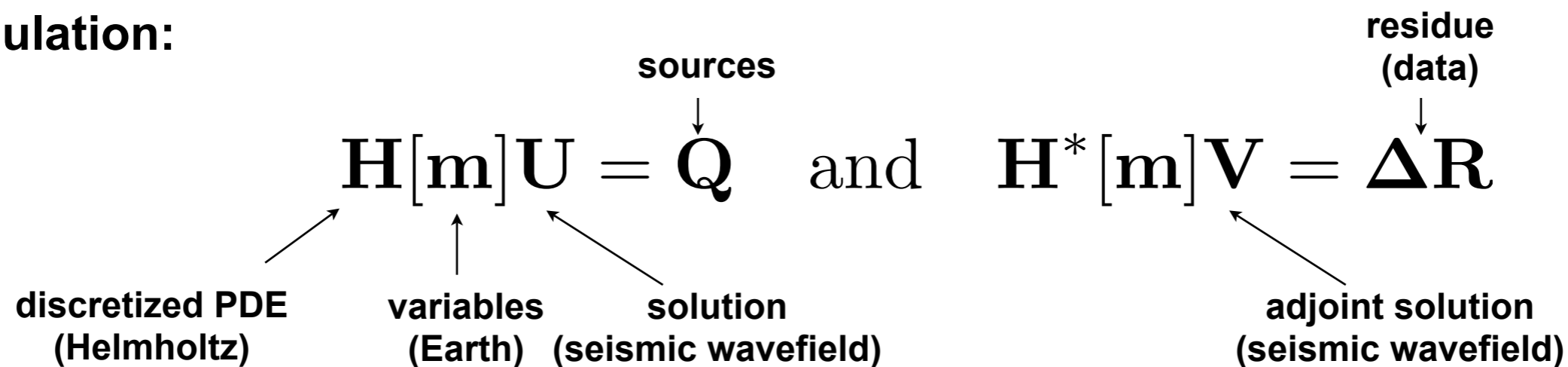
Imaging:

$$\begin{aligned} \text{image volume} &\downarrow \\ \widehat{\delta\mathbf{I}}(x_s, x_r, \omega) &= (\mathbf{U} \circ \mathbf{V}^*) \\ \delta\mathbf{m}(x_s = x_r, t = 0) &= \sum_{\omega} \omega^2 \text{diag}\{\widehat{\delta\mathbf{I}}\} \end{aligned}$$

multi-D
'cross-correlation'
↓

Essentials of seismic inversion

Simulation:



- High-dimensional solutions are **extremely** expensive to compute
- Inversion (e.g. via Gauss-Newton) requires multiple solves
- Number of blocks in \mathbf{H} and number of **rhs** determine simulation & acquisition costs

Imaging:

image volume \downarrow $\hat{\delta\mathbf{I}}(x_s, x_r, \omega)$
 multi-D 'cross-correlation' \downarrow $(\mathbf{U} \circ \mathbf{V}^*)$

$$\delta\mathbf{m}(x_s = x_r, t = 0) = \sum_{\omega} \omega^2 \text{diag}\{\hat{\delta\mathbf{I}}\}$$

- Explicit matrix evaluations part of prestack migration are expensive, require lots of memory
- Improve recovery by formulating imaging as a CSed inversion problem where
 - *off diagonals are penalized* (impose focusing)
 - image recovered by wavefield inversion by **joint sparsity** promotion

Imaging by wavefield correlations

Creation of image volumes involves

$$\delta \mathbf{I}(x_s, x_r, t) = \mathbf{F}_t^* \sum_{\omega} \omega^2 (\mathbf{U} \circ \mathbf{V}^*)$$

with

$$(\mathbf{U} \circ \mathbf{V}^*) = \begin{bmatrix} \bar{\mathbf{U}}_1 & & & \\ & \ddots & & \\ & & \bar{\mathbf{U}}_{n_f} & \\ & & & \end{bmatrix} \begin{bmatrix} \mathbf{V}_1^T \\ \vdots \\ \mathbf{V}_{n_f}^T \end{bmatrix}$$

and

$$\mathbf{U}_f = [\mathbf{u}_1 \cdots \mathbf{u}_{n_f}] \text{ and } \mathbf{V}_f = [\mathbf{v}_1 \cdots \mathbf{v}_{n_f}]$$

- Extremely *large* problem size
- Gradient updates do not account for the *Hessian*
- Recast imaging into a multi-D *deconvolution* problem supplemented by *focussing*
- Penalize *off-diagonals* as part of this *focussing* procedure

Wavefield focusing

Define linear mid-point/offset coordinate transformation

$$\delta\mathbf{I}'(m, h, t) = \mathbf{T}_{(x_s, x_r) \mapsto (m, h)}^{\Delta h} \delta\mathbf{I}(x_s, x_r, t),$$

$$\text{with } m = \frac{1}{2}(x_s + x_r) \quad \text{and} \quad h = \frac{1}{2}(x_s - x_r)$$

Penalize **defocusing** via minimizing [Symes, '09]

$$\|\mathbf{P}_h \mathbf{I}'(\cdot, h)\|_2 \quad \text{with } \mathbf{P}_h \cdot = \mathbf{h} \cdot$$

an *annihilator* that increasingly *penalizes* non-zero offsets.

Remark: conventional imaging principle

$$\delta\mathbf{m} = \delta\mathbf{I}'(\cdot, h = 0, t = 0)$$

Wavefield inversion with focusing

Form augmented linear system

$$\begin{aligned}(\mathbf{U}^* \circ \mathbf{S}^* \mathbf{X}) &\approx \mathbf{V}^* \\ P_h \mathbf{X} &\approx \mathbf{0} \quad \text{focuses}\end{aligned}$$

with the sparsifying transform (curvelets/wavelets along depth-midpoint slices)

$$\mathbf{S} \cdot := \text{vec}^{-1} \left((\mathbf{Id} \otimes \mathbf{C}) \mathbf{T}_0 \right) \text{vec} (\cdot) \cdot$$

and \mathbf{T}_0 source/receiver-midpoint offset mapping supplemented with the imaging condition for $t=0$.

Formulation by *wavefield inversion* is a two-edged sword:

- Correct for amplitudes by wavefield inversion
- Reduce system size by compressive sampling ...

System-size reduction by CS

For each angular frequency, randomly subsample with CS matrix

$$\mathbf{RM} := \overbrace{\begin{bmatrix} \mathbf{R}_1^\sigma \otimes \mathbf{R}_1^\rho \otimes \mathbf{R}_1^\zeta \\ \vdots \\ \mathbf{R}_{n'_f}^\sigma \otimes \mathbf{R}_{n'_f}^\rho \otimes \mathbf{R}_{n'_f}^\zeta \end{bmatrix}}^{\text{sub sampler}} \overbrace{\left(\mathbf{F}_3^* \left(e^{i\theta} \right) \right) \mathbf{F}_3}_{\text{random phase encoder}},$$

$\theta_w = \text{Uniform}([0, 2\pi])$

with

$$n'_f \times n'_\sigma \times n'_\rho \times n'_\zeta \ll n_f \times n_s \times n_r \times n_z$$

Model-space CS subsampling along source, receiver, and depth coordinates.

Compressive wavefield inversion with focussing

Compressively sample *augmented* system

$$\begin{aligned} \mathbf{RM}(\mathbf{U}^* \circ \mathbf{S}^* \mathbf{X}) &\approx \mathbf{RMV}^T && \text{or} && \mathbf{AX} \approx \mathbf{B} \\ \mathbf{P}_h \mathbf{X} &\approx \mathbf{0} \end{aligned}$$

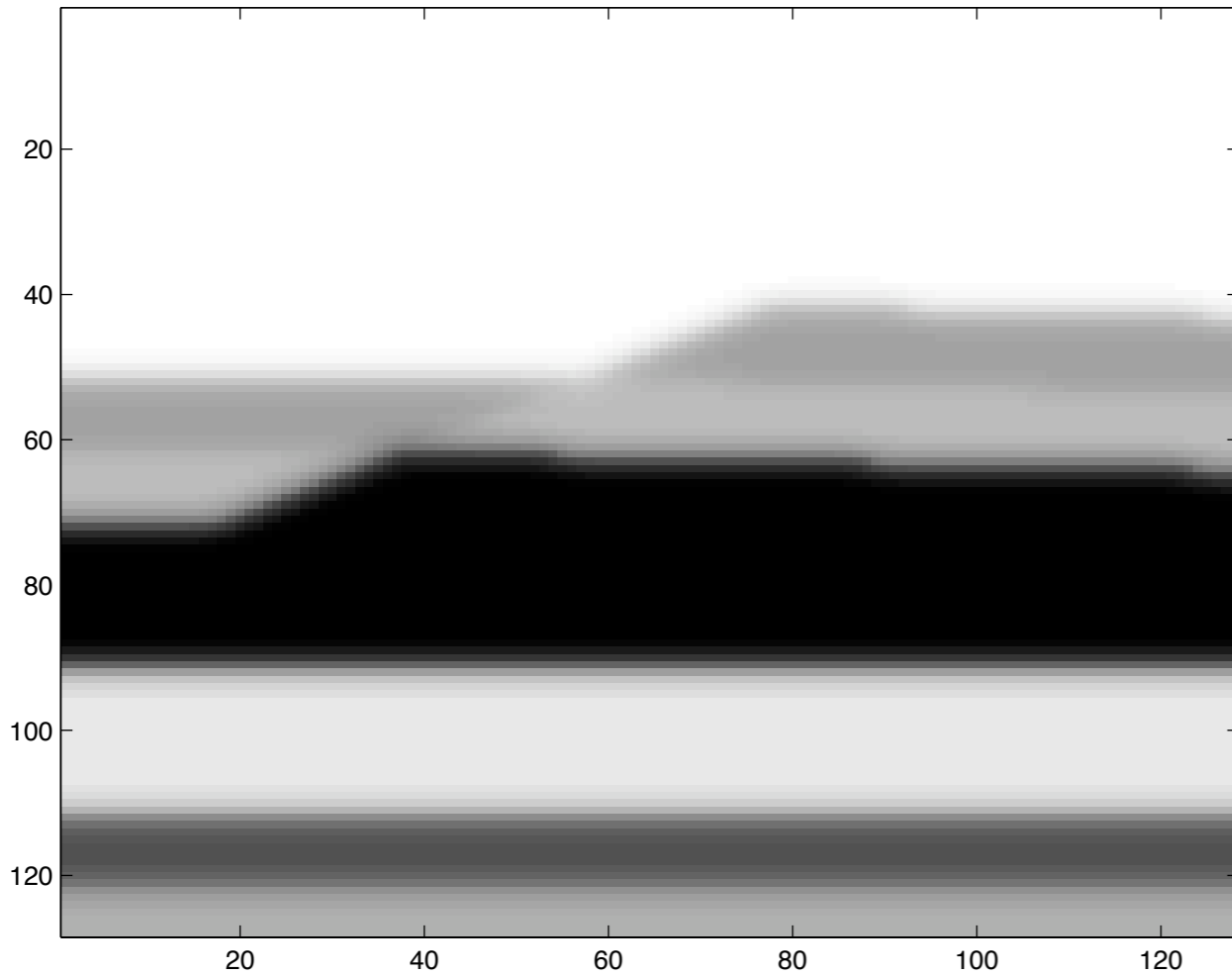
Recover focused solution by mixed (1,2)-norm minimization

$$\tilde{\mathbf{X}} = \arg \min_{\mathbf{X}} \|\mathbf{X}\|_{1,2} \quad \text{subject to} \quad \|\mathbf{AX} - \mathbf{B}\|_{2,2} \leq \sigma,$$

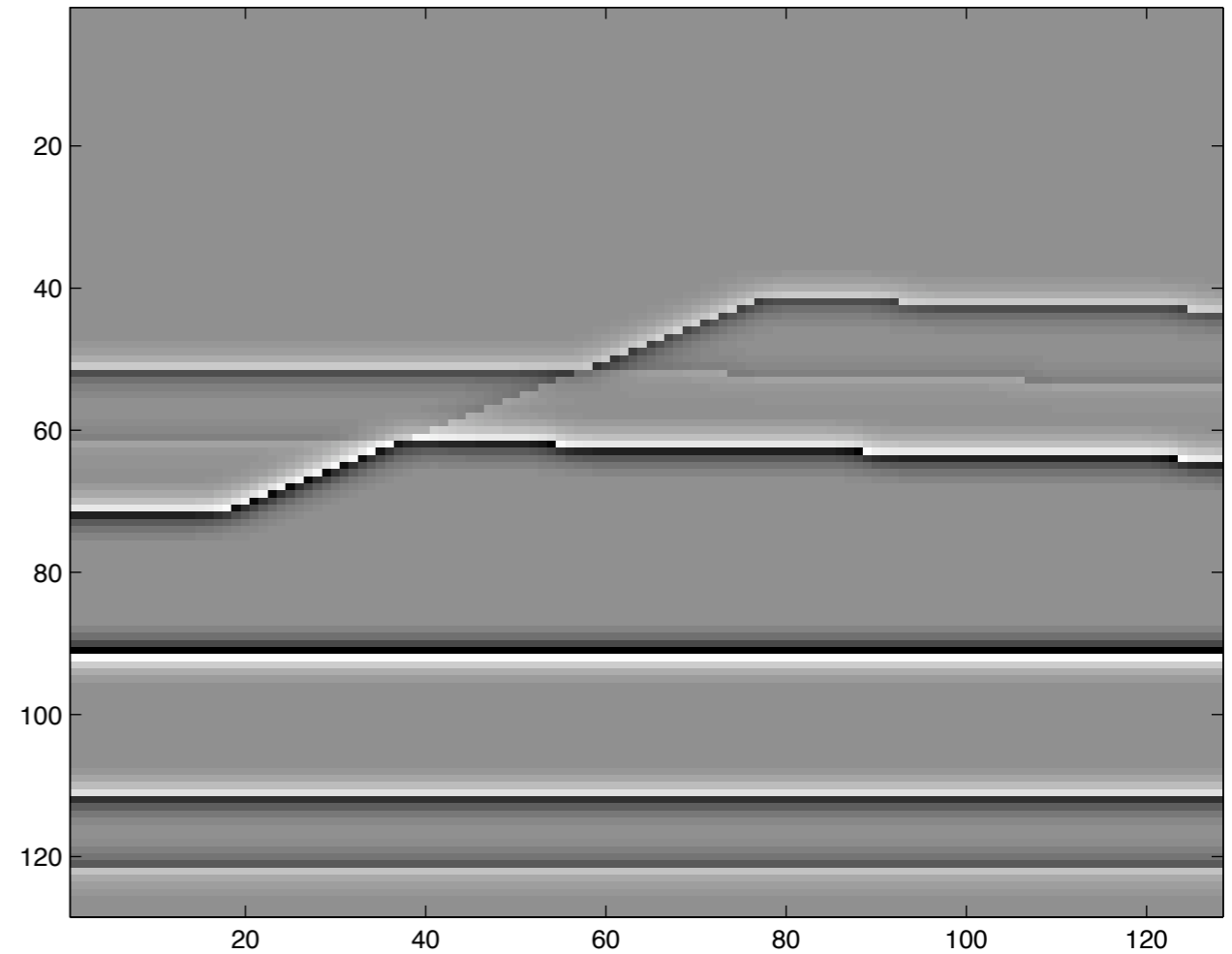
with
$$\|\mathbf{X}\|_{1,2} := \sum_{i \in \text{rows}(\mathbf{X})} \|\text{row}_i(\mathbf{X})^*\|_2$$

and
$$\|\mathbf{X}\|_{2,2} := \left(\sum_{i \in \text{rows}(\mathbf{X})} \|\text{row}_i(\mathbf{X})^*\|_2^2 \right)^{\frac{1}{2}}.$$

Stylized example



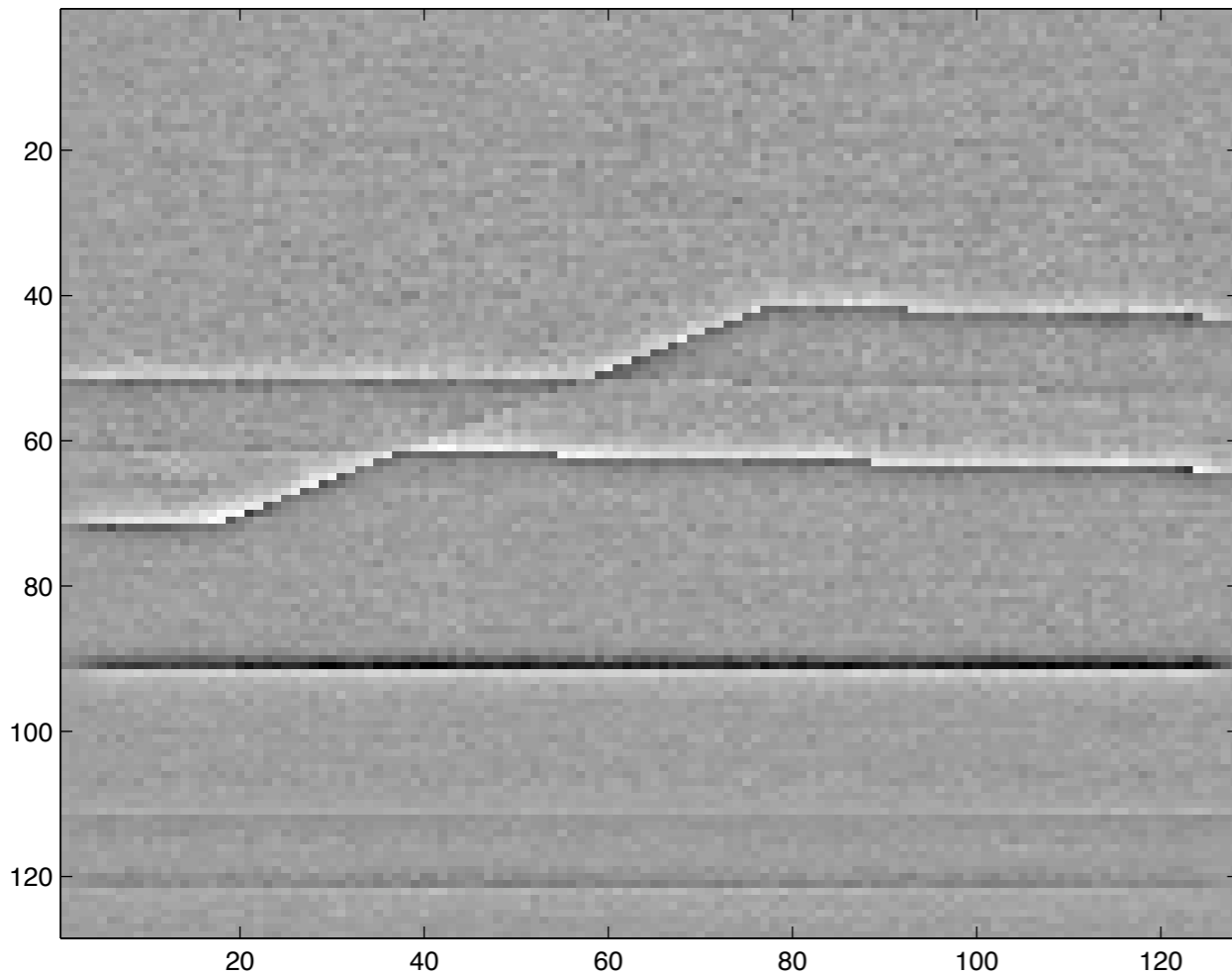
background velocity model



perturbation

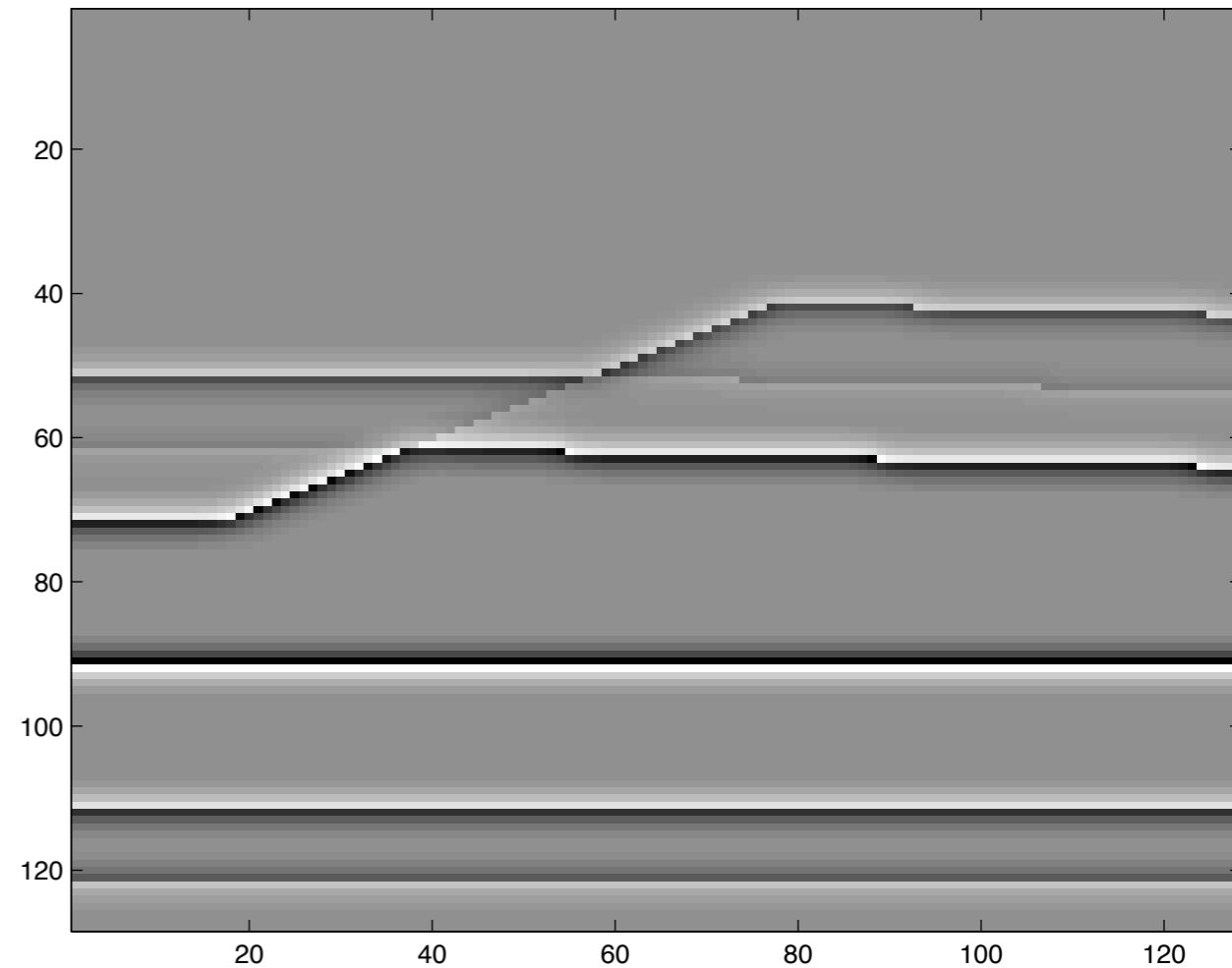
Stylized example

migrated CS image



plain migration

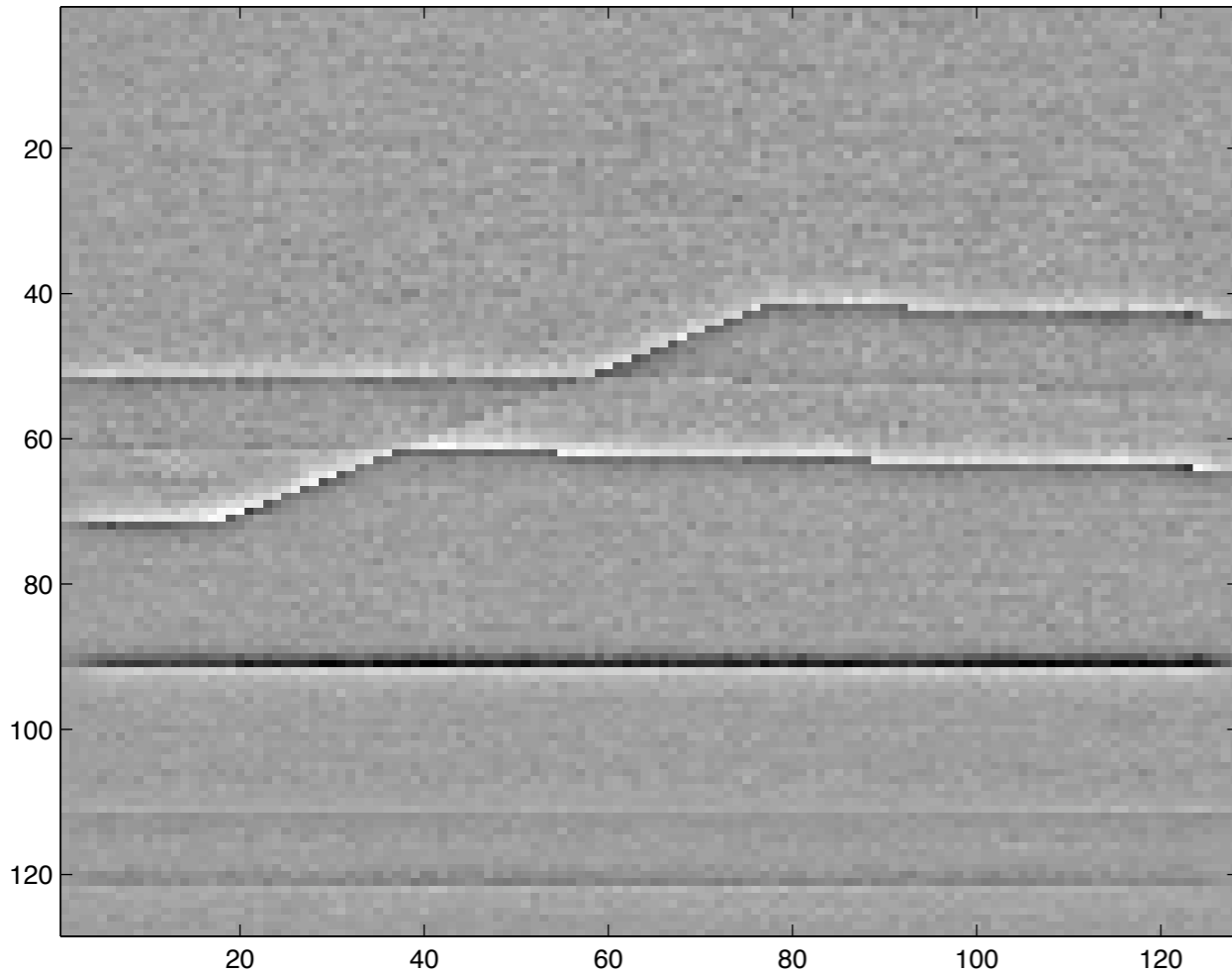
inverted CS image



wavefield inversion

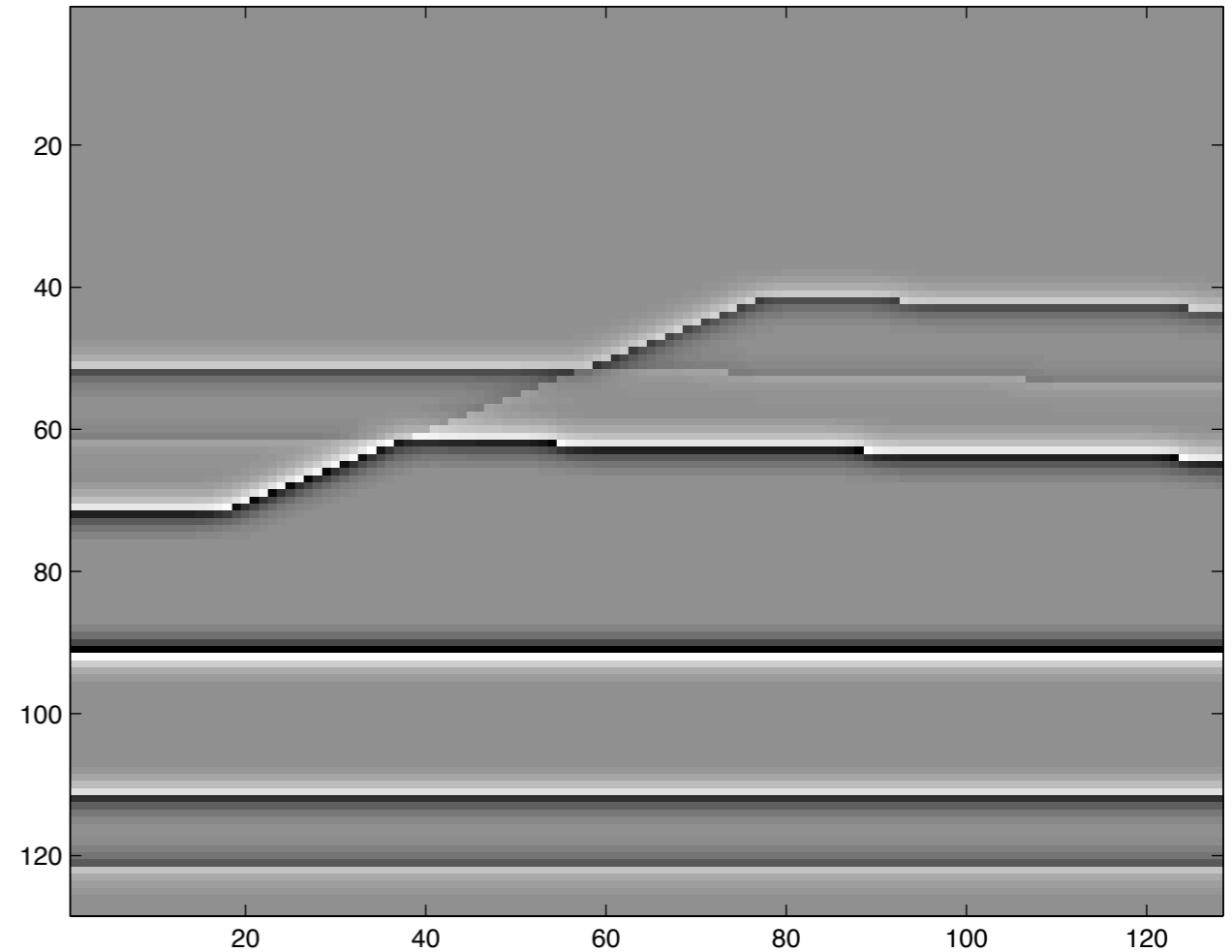
Stylized example

migrated CS image



plain migration

inverted CS image

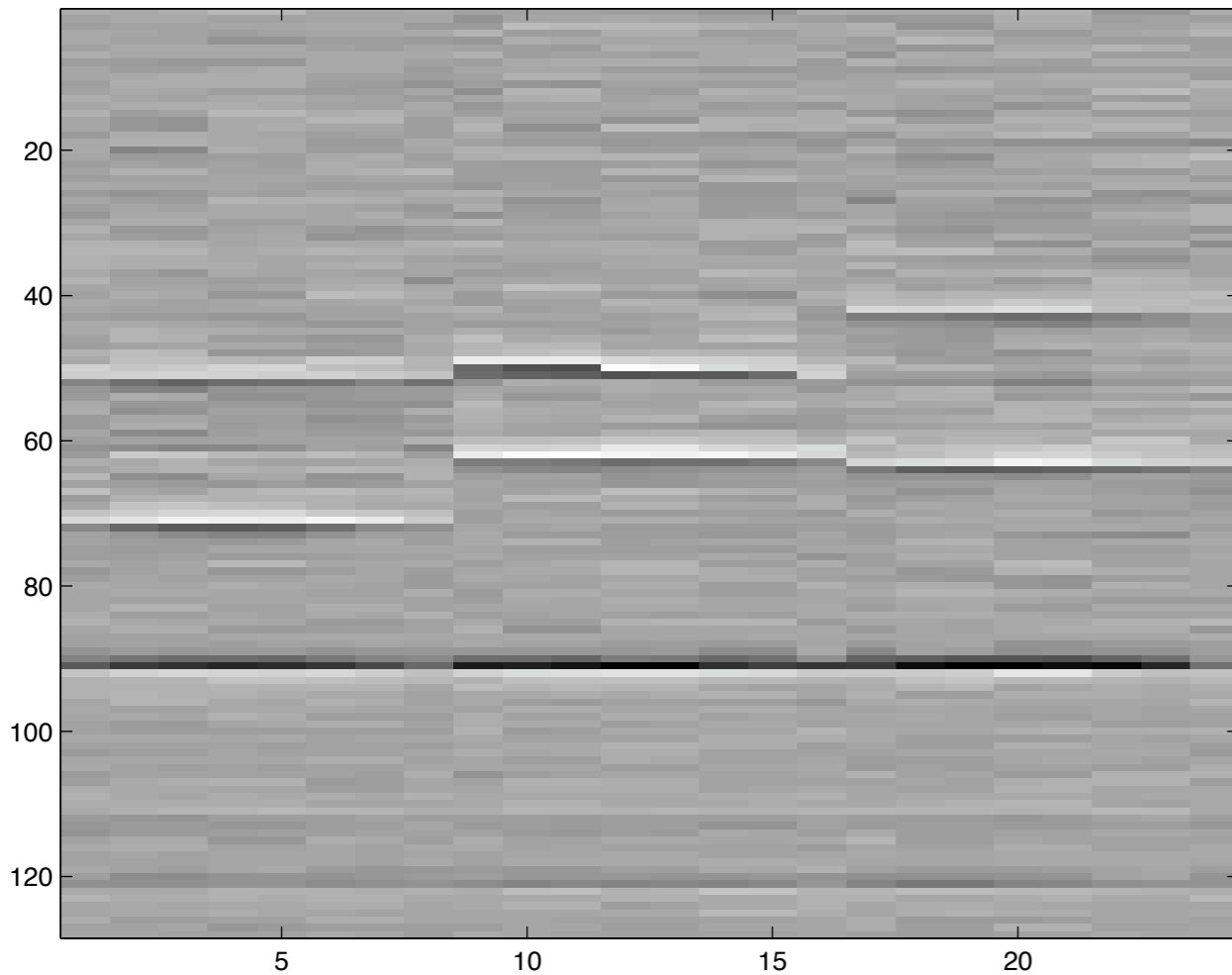


wavefield inversion

Recovery from 64-fold subsampling ...

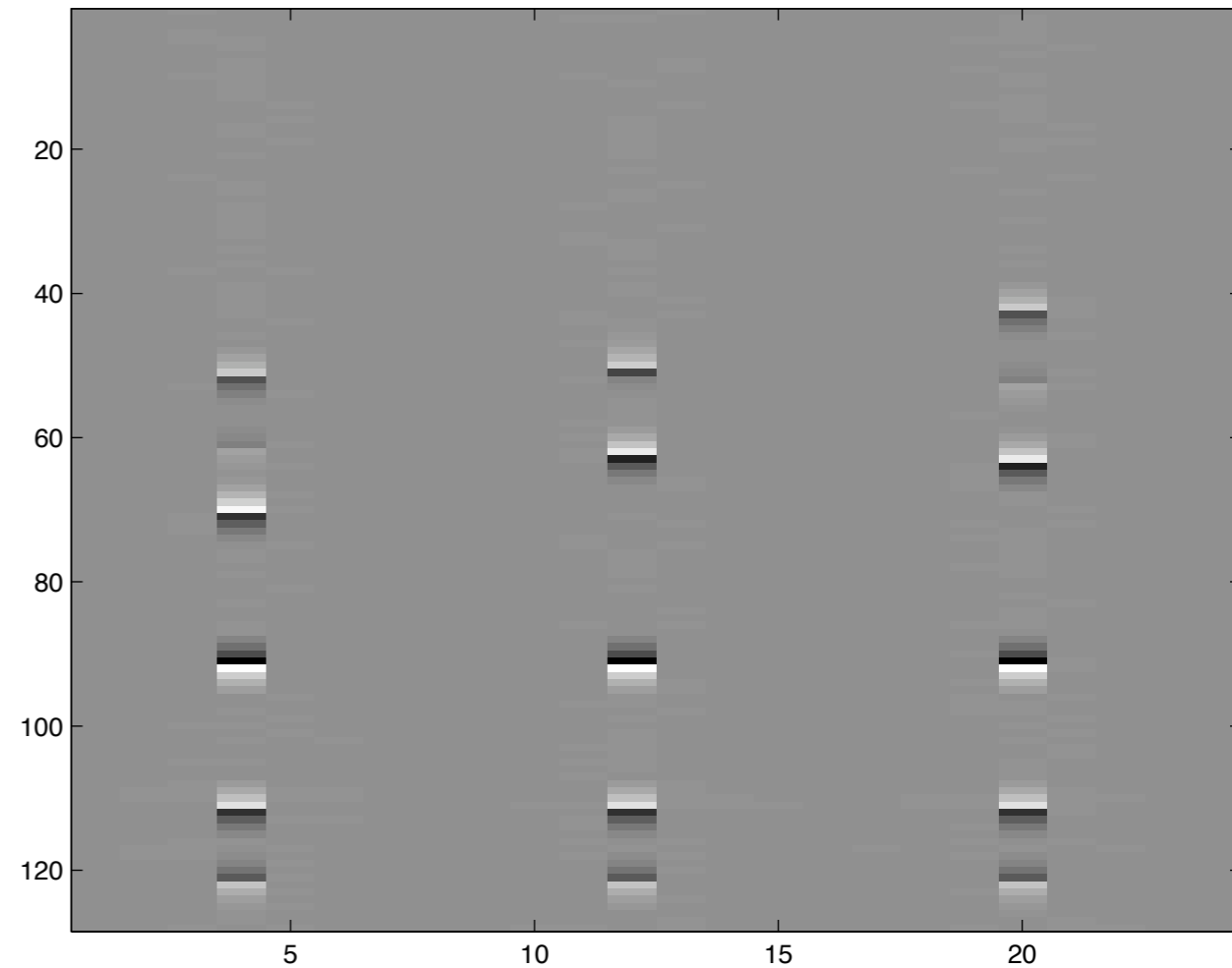
Stylized example

migrated CS cigs



correlation based

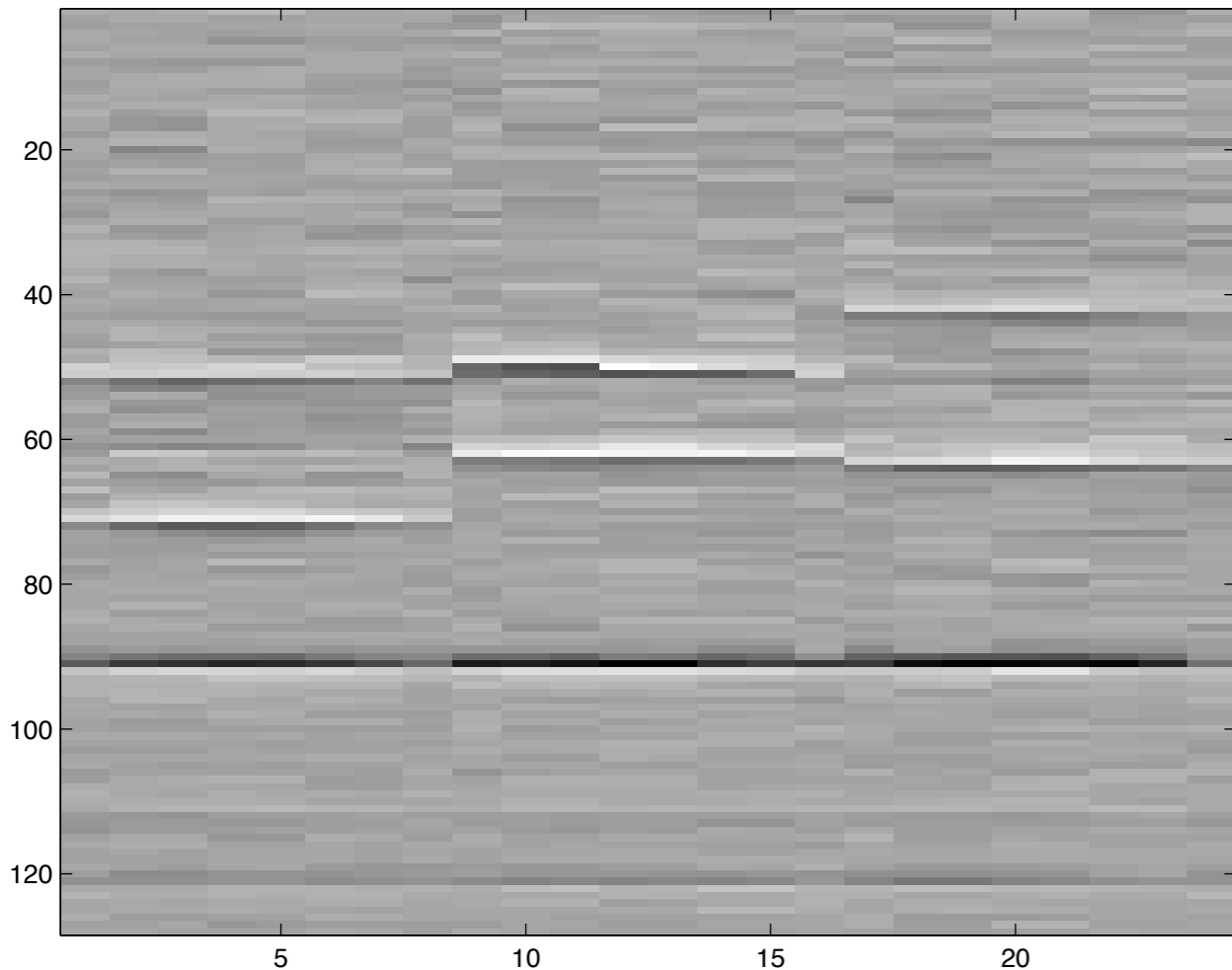
inverted CS cigs



wavefield inversion

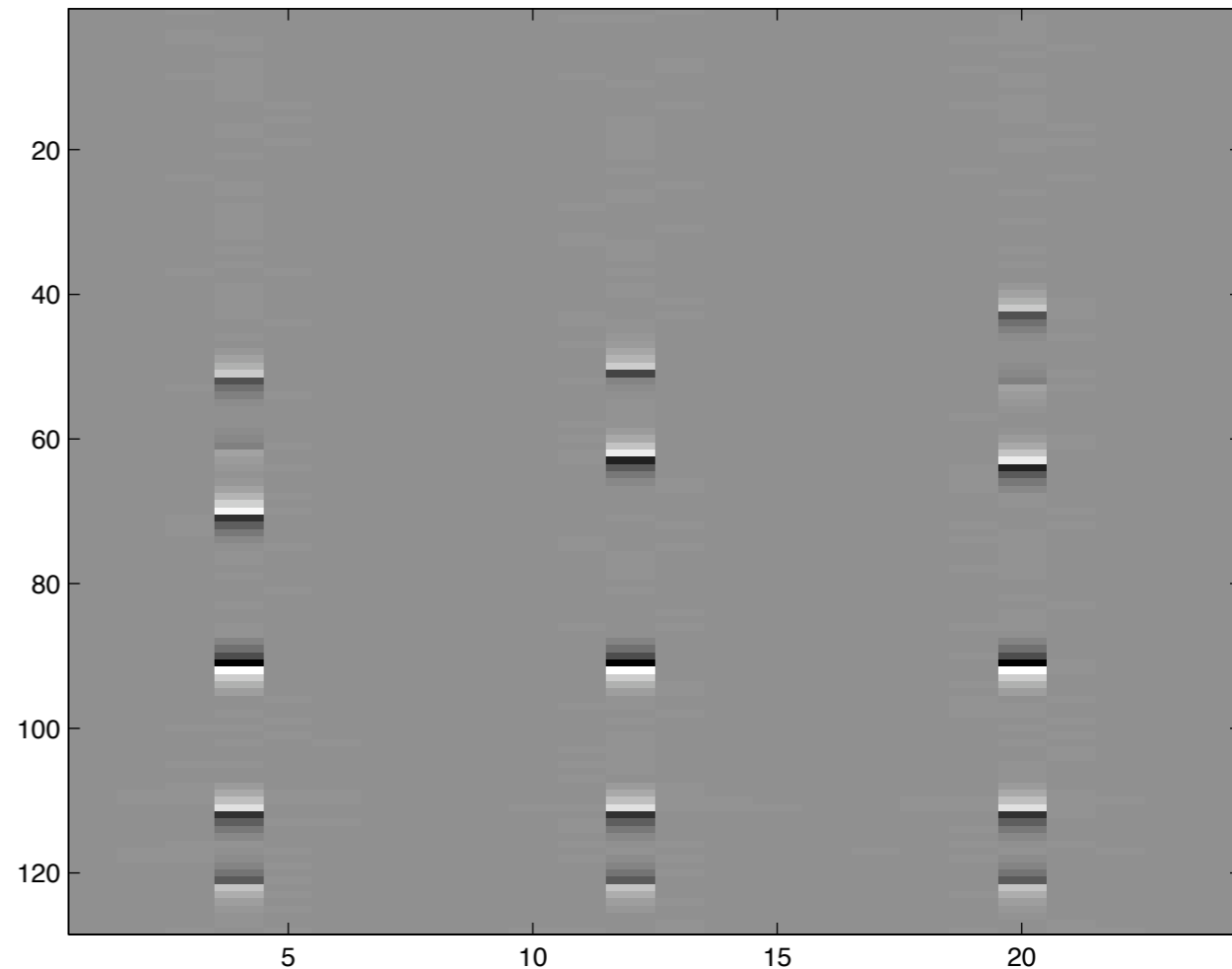
Stylized example

migrated CS cigs



correlation based

inverted CS cigs



wavefield inversion

Common-image gathers are focussed.

Observations

- **CS** provides a **new linear sampling paradigm** based on **randomization**
 - **reduces** data volumes and hence **acquisition, processing & inversion costs**
 - **linearity** allows for compressive processing & inversion
- **CS** leads to
 - “acquisition” of *smaller* data volumes that carry the **same information** or
 - to **improved inferences** from data using the *same* resources
 - **concrete implementations**
- **CS** combined with physics improved recovery by using
 - compressively-sampled multiples
 - focusing in the image space
- **Bottom line: acquisition & processing & inversion costs** are no longer determined by the **size** of the **discretization** but by **transform-domain sparsity** of the **solution ...**

Acknowledgments

- E. van den Berg and M. P. Friedlander for *SPGL1* (www.cs.ubc.ca/labs/scl/spgl1) & *Sparco* (www.cs.ubc.ca/labs/scl/sparco)
- Sergey Fomel and Yang Liu for Madagascar (rsf.sf.net)
- E. Candes and the Curvelab team

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and... Thank you!