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Simply denoise: wavefield reconstruction via jittered undersampling

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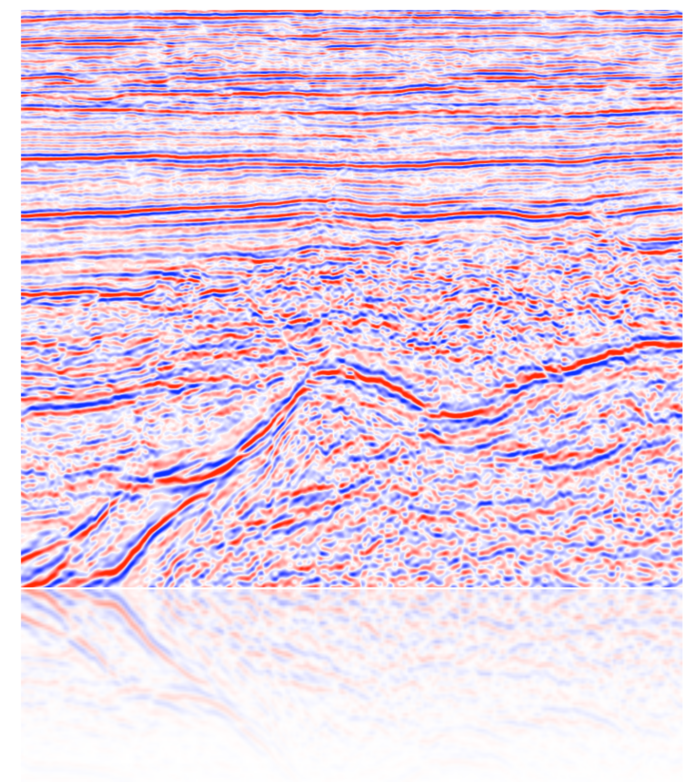

SLIM consortium meeting
Seismic wavefield reconstruction
Wednesday, February 20th, 2008 - 2:00 PM

[Hennenfent and Herrmann, 2008]

THE UNIVERSITY OF BRITISH COLUMBIA | VANCOUVER

Unleash the power of random sampling...

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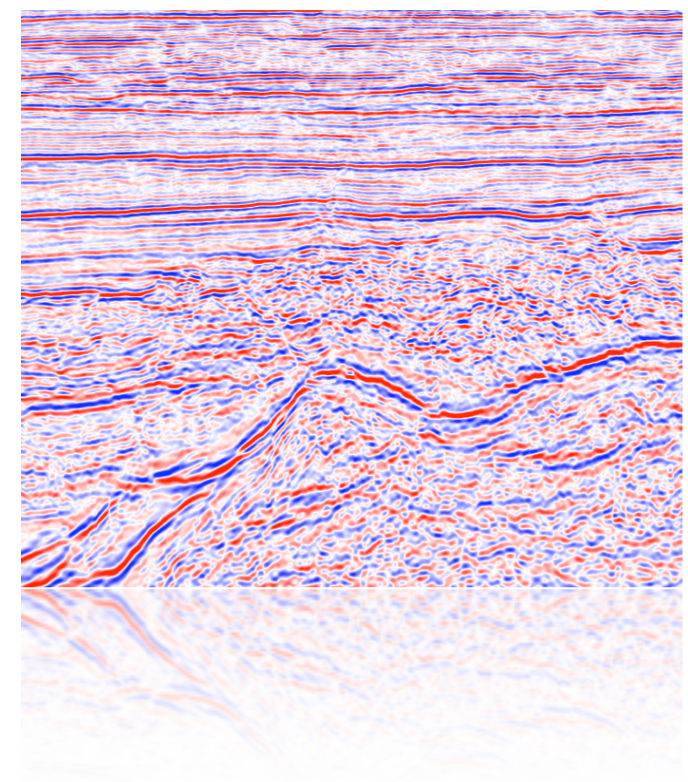

SLIM consortium meeting
Seismic wavefield reconstruction
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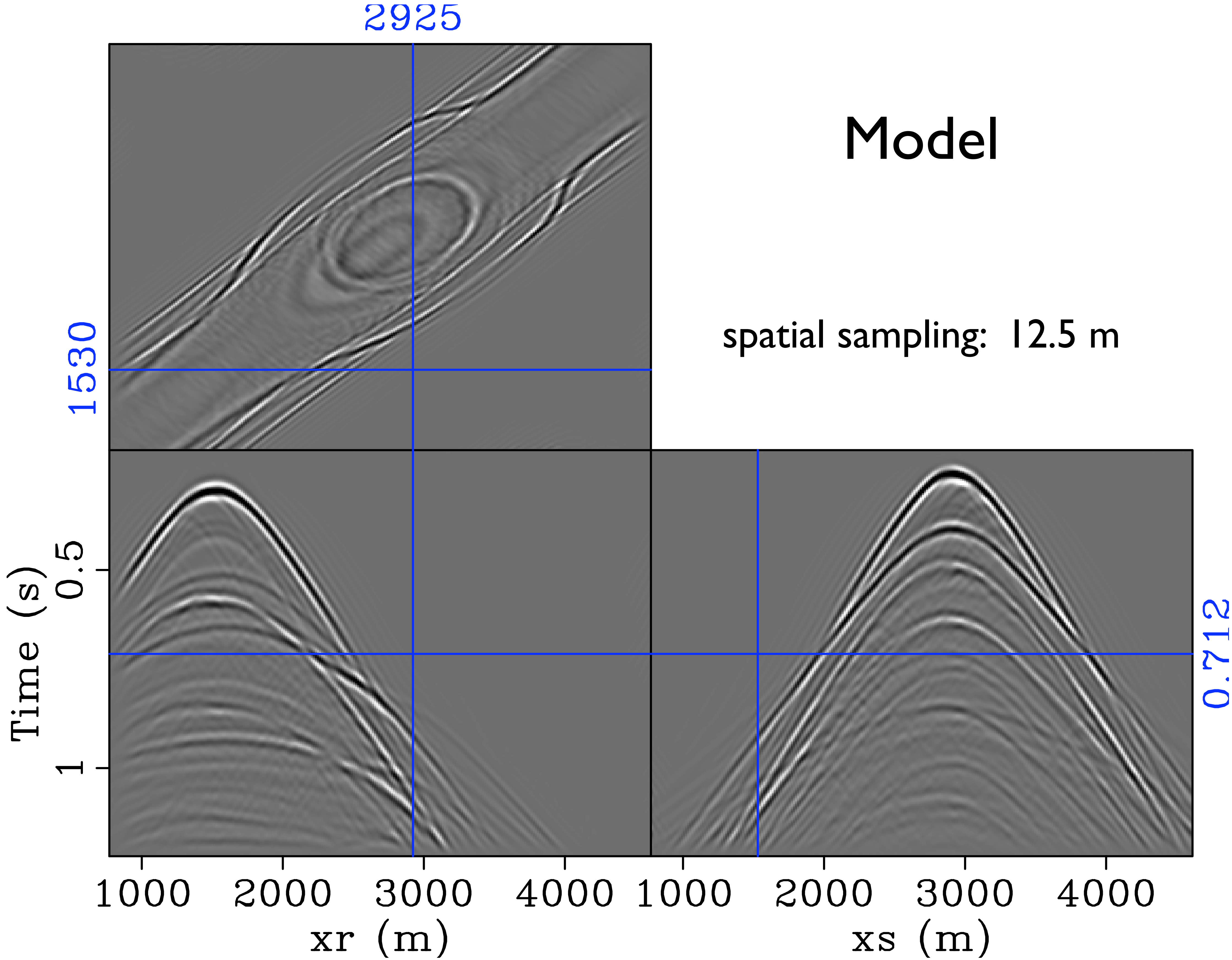
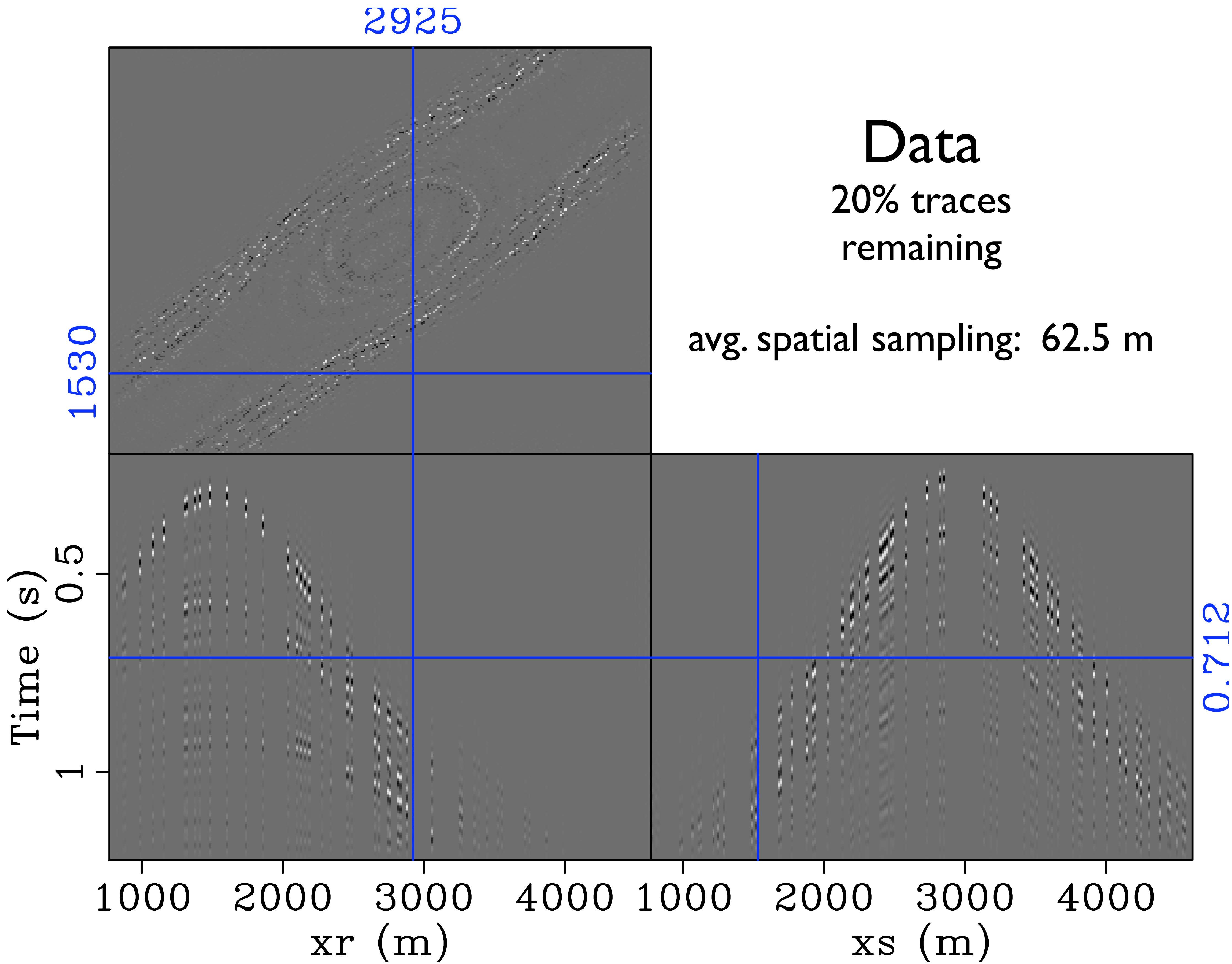
[Hennenfent and Herrmann, 2008]

Model

spatial sampling: 12.5 m



Seismic Laboratory for Imaging and Modeling



Data

20% traces remaining

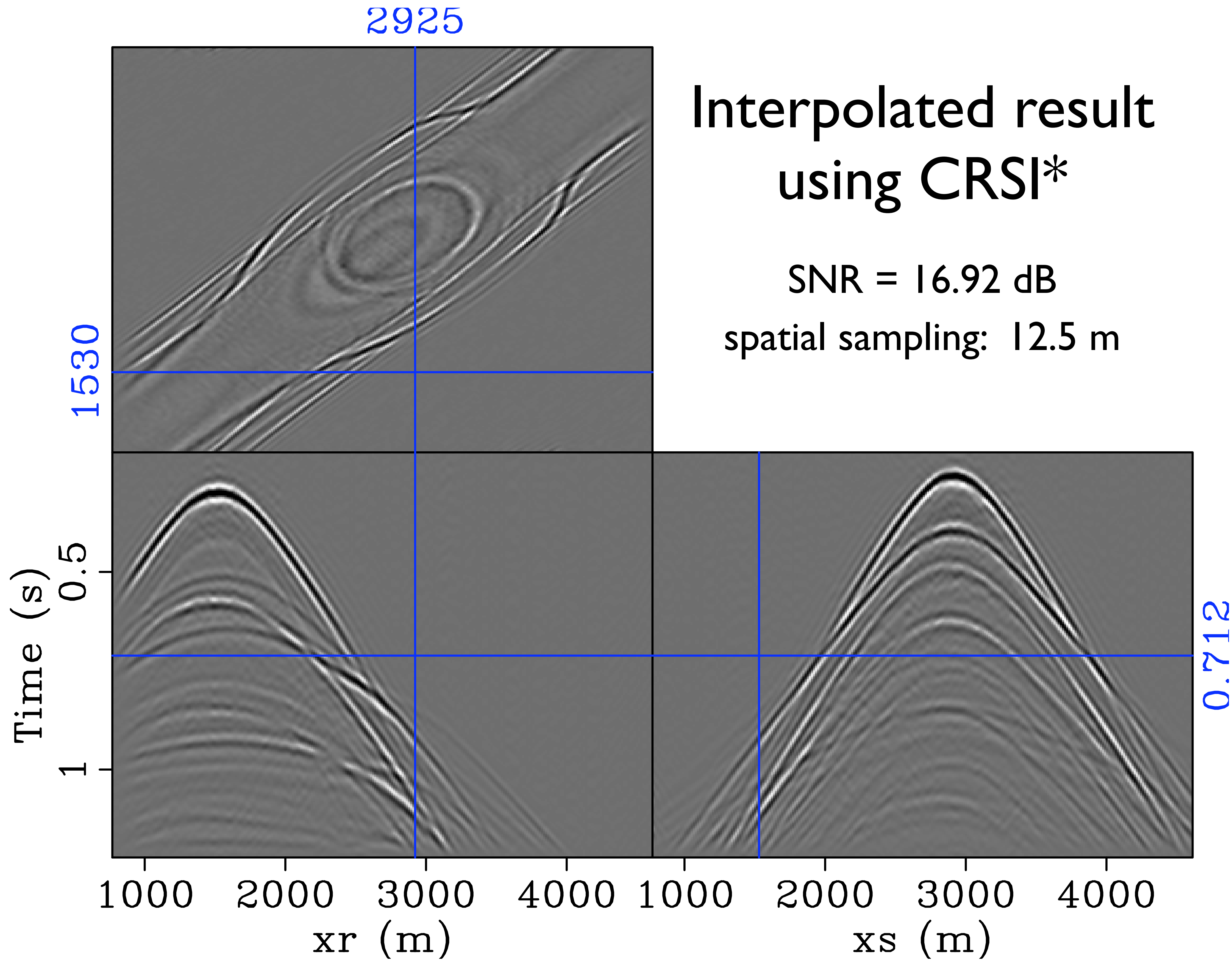
avg. spatial sampling: 62.5 m

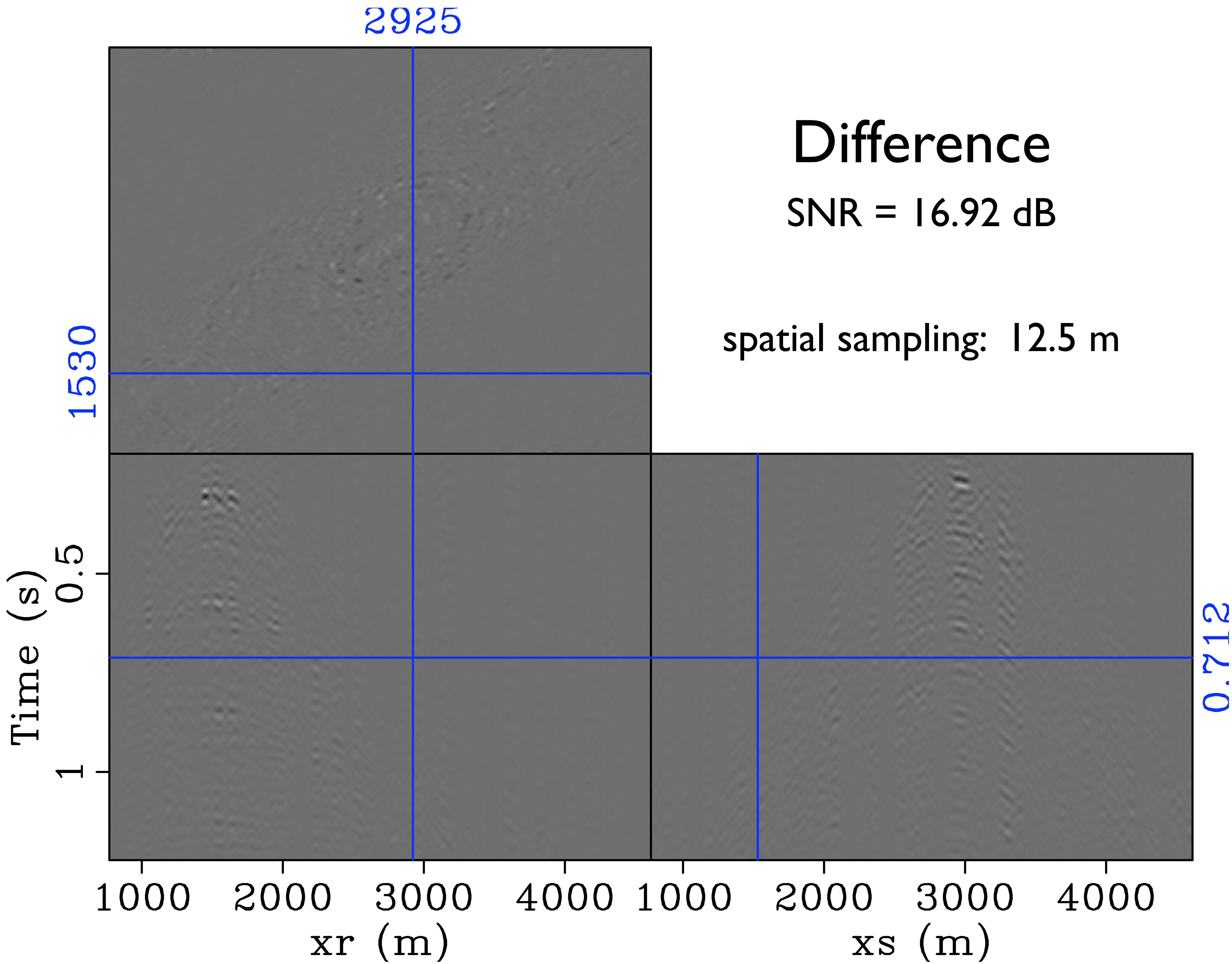
* **CRSI**: Curvelet Reconstruction with Sparsity-promoting Inversion

Interpolated result using CRSI*

SNR = 16.92 dB

spatial sampling: 12.5 m

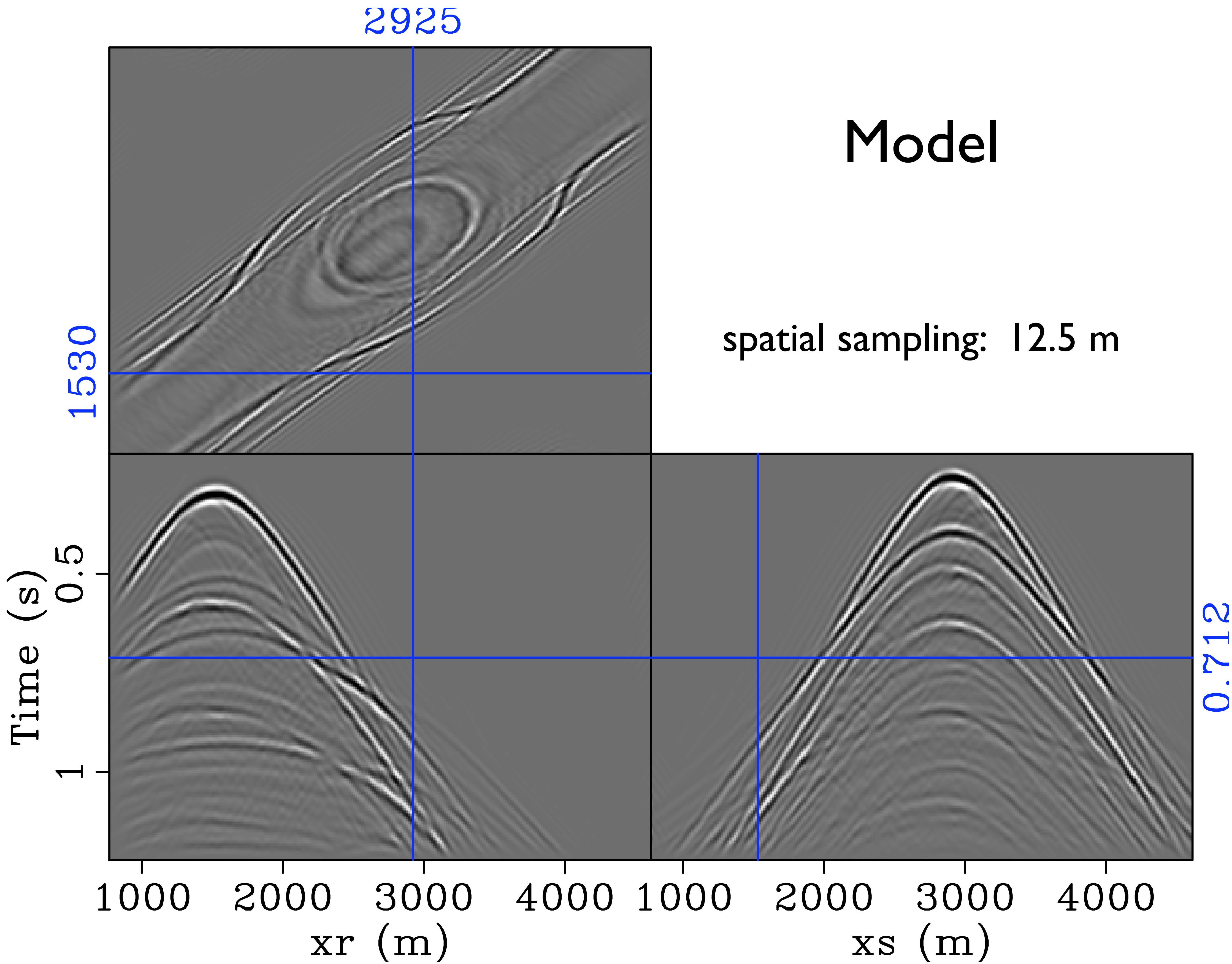




Difference

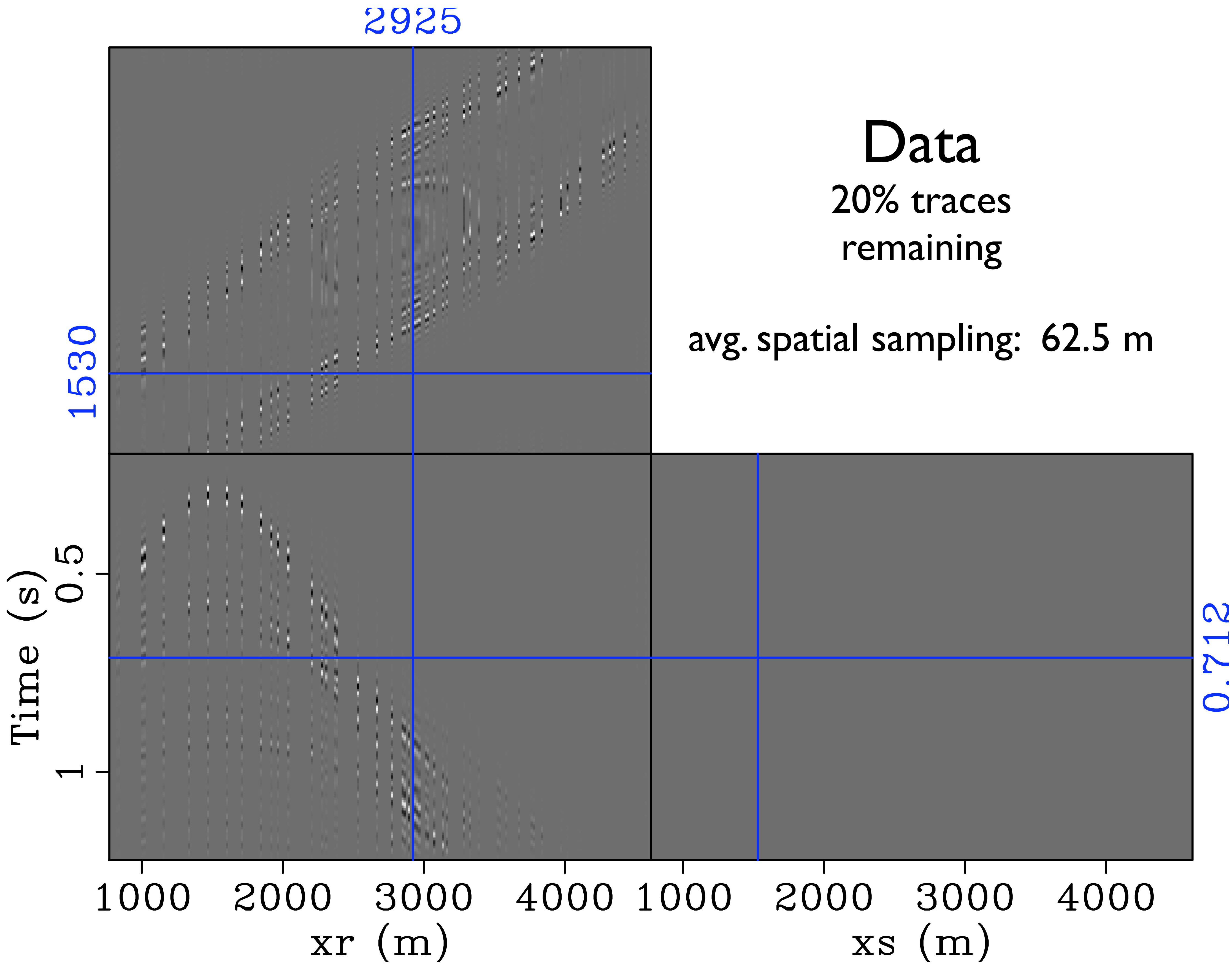
SNR = 16.92 dB

spatial sampling: 12.5 m



Model

spatial sampling: 12.5 m



Data

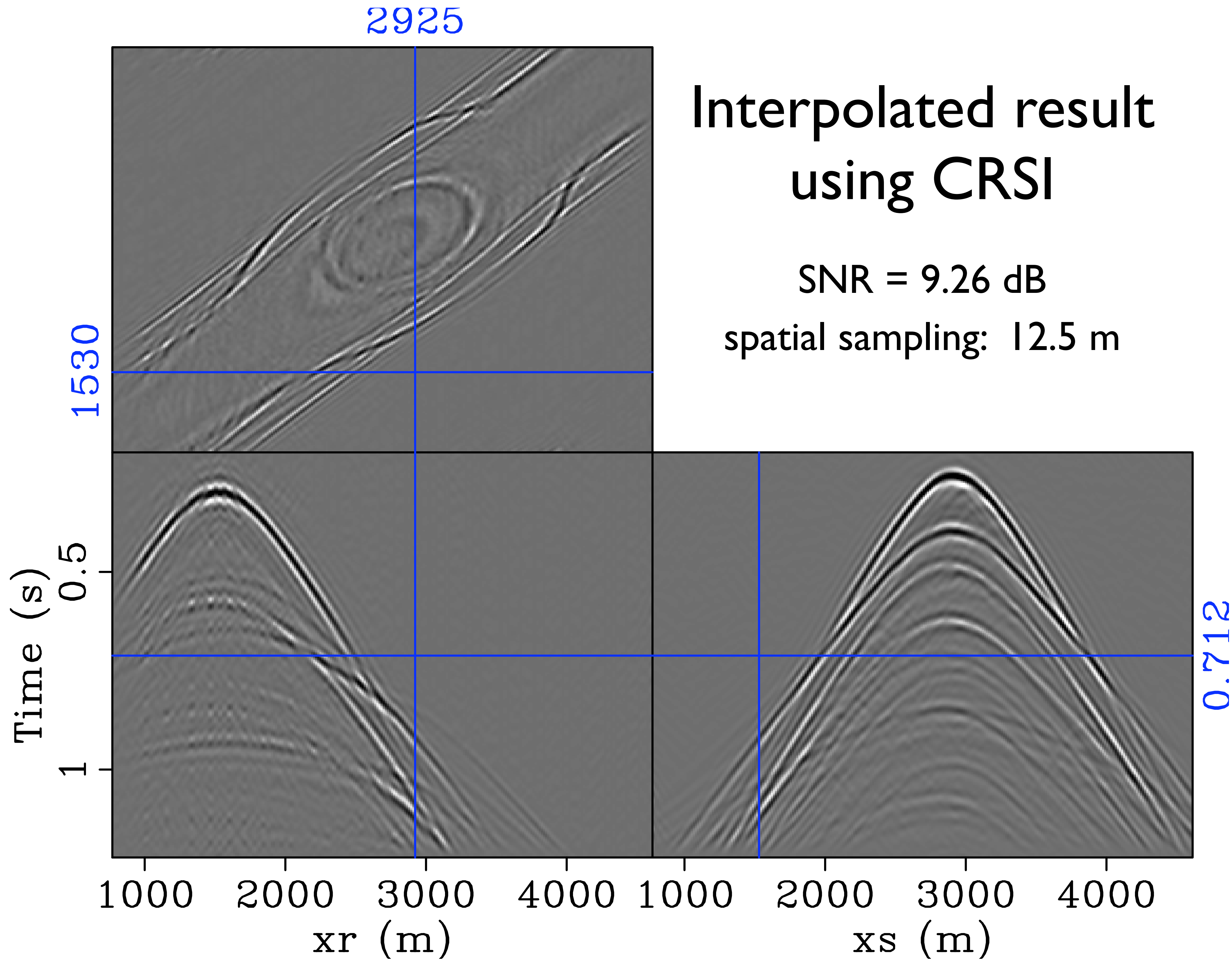
20% traces remaining

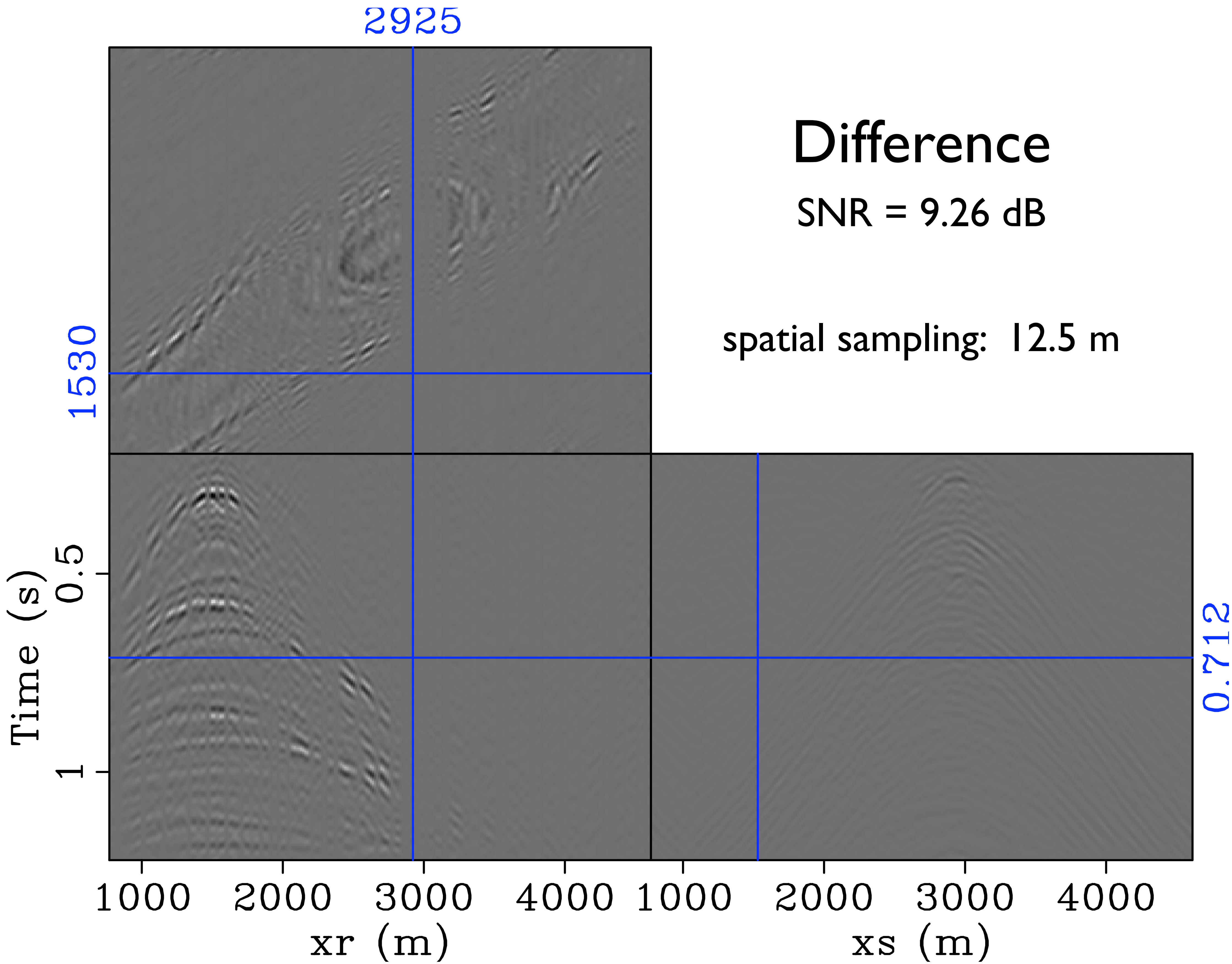
avg. spatial sampling: 62.5 m

Interpolated result using CRSI

SNR = 9.26 dB

spatial sampling: 12.5 m





Difference

SNR = 9.26 dB

spatial sampling: 12.5 m

Motivation

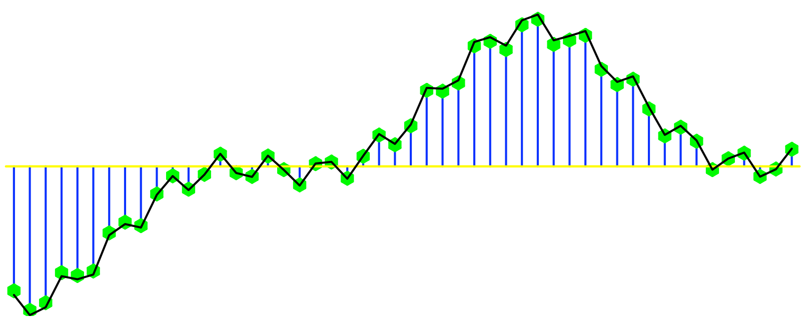
- preliminary observations
  - 5-fold undersampled data in the time-source-receiver volume
    - missing traces at *irregular source-receiver locations*: **good reconstruction!**
    - missing traces at *irregular receiver locations*: **(much) less accurate reconstruction…**

- questions
  - what makes one case better than the other?
  - are acquisition irregularities really harmful to processing and imaging?
  - is there something to learn about favorable coarse acquisition geometries?
  - can the success of an interpolation method be (accurately) predicted based on the acquisition geometry?

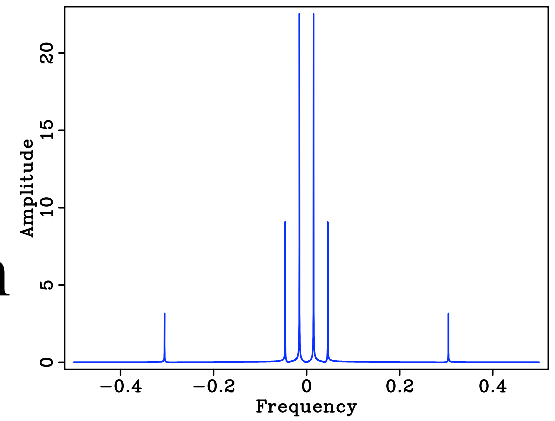
Previous art

- geophysical literature
  - Bednar, J. B., 1996, Coarse is coarse of course unless… The Leading Edge, **15**, 763 - 764.
  - Sun, Y., G. T. Schuster, and K. Sikorski, 1997, A quasi-Monte Carlo approach to 3D migration: Theory: Geophysics, **62**, 918 - 928.
  - Trad, D. O., and T. J. Ulrych, 1999, Radon transform: beyond aliasing with irregular sampling, 6th International Congress of the Brazilian Geophysical Society.
  - Abma, R. and N. Kabir, 2006, 3D interpolation of irregular data with a POCS algorithm: Geophysics, **71**, E91 – E97.
  - Zwartjes, P. M. and M. D. Sacchi, 2007, Fourier reconstruction of nonuniformly sampled, aliased data: Geophysics, **72**, V21–V32.
- other fields
  - Donoho, D. L., Y. Tsaig, I. Drori, and J.-L. Starck, 2006, Sparse solution of underdetermined linear equations by stagewise orthogonal matching pursuit: Technical report, Stanford Statistics Department. TR-2006-2.
  - Dippe, M. and E. Wold, 1992, Stochastic sampling: theory and application: Progress in computer graphics, **1**, 1 – 54.

Simple example

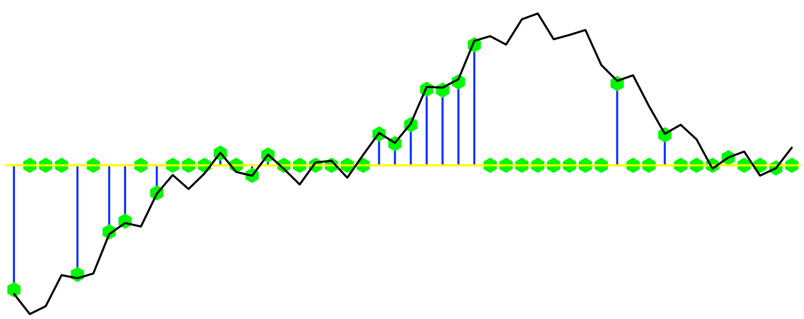


Fourier → transform

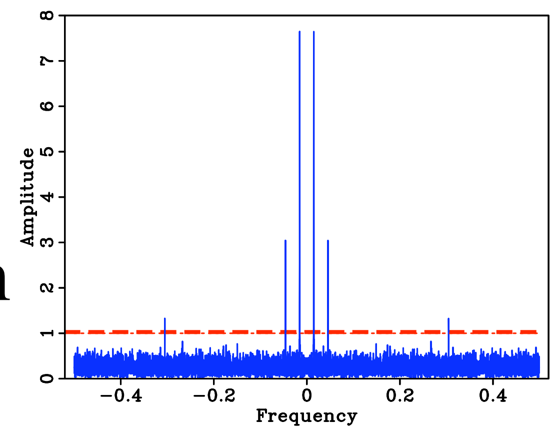


few significant coefficients

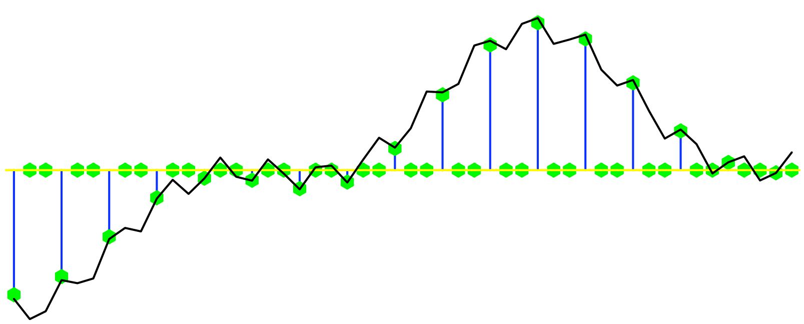
3-fold under-sampling



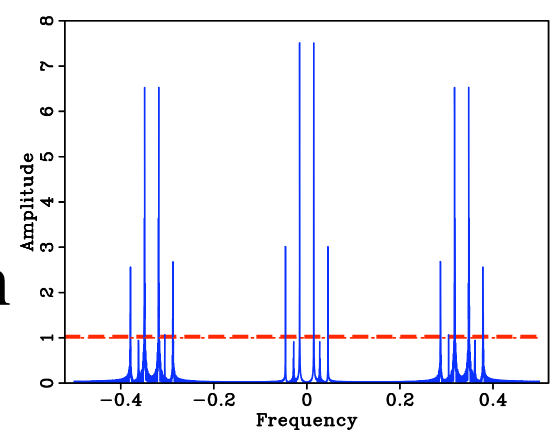
Fourier → transform



✓ significant coefficients detected



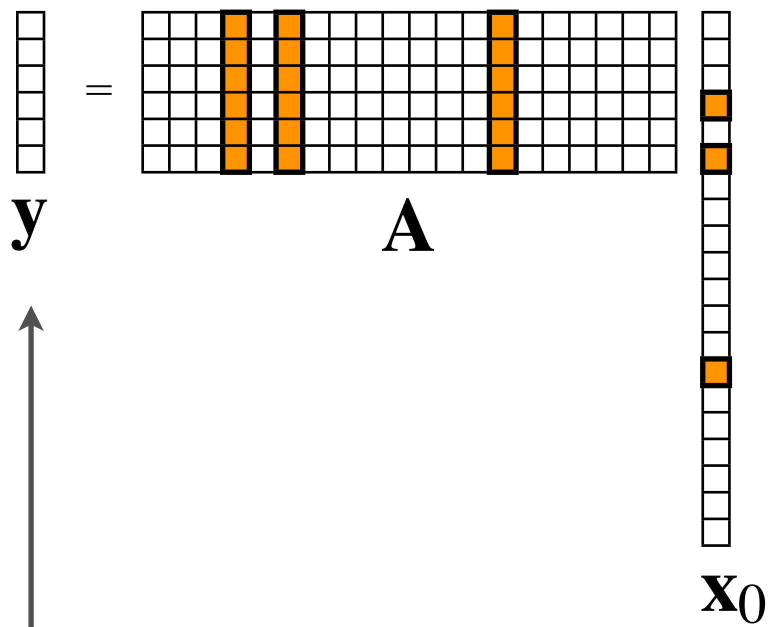
Fourier → transform



✗ ambiguity

Forward problem

restriction operator

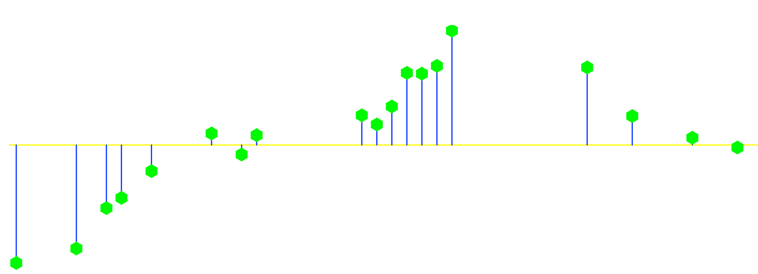


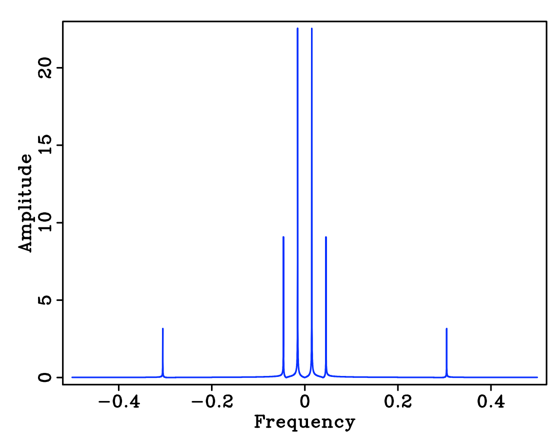
with $\mathbf{A} := \mathbf{R}\mathbf{F}^H$

Fourier transform

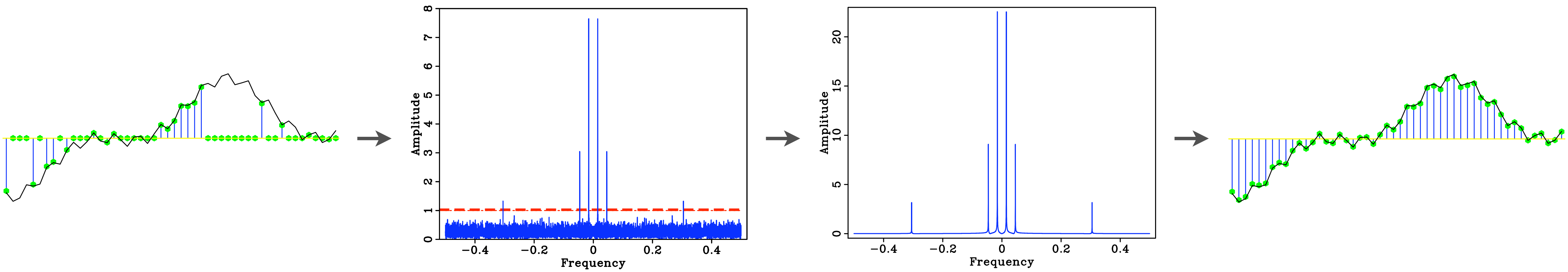
signal

Fourier coefficients (**sparse**)





Naive sparsity-promoting recovery

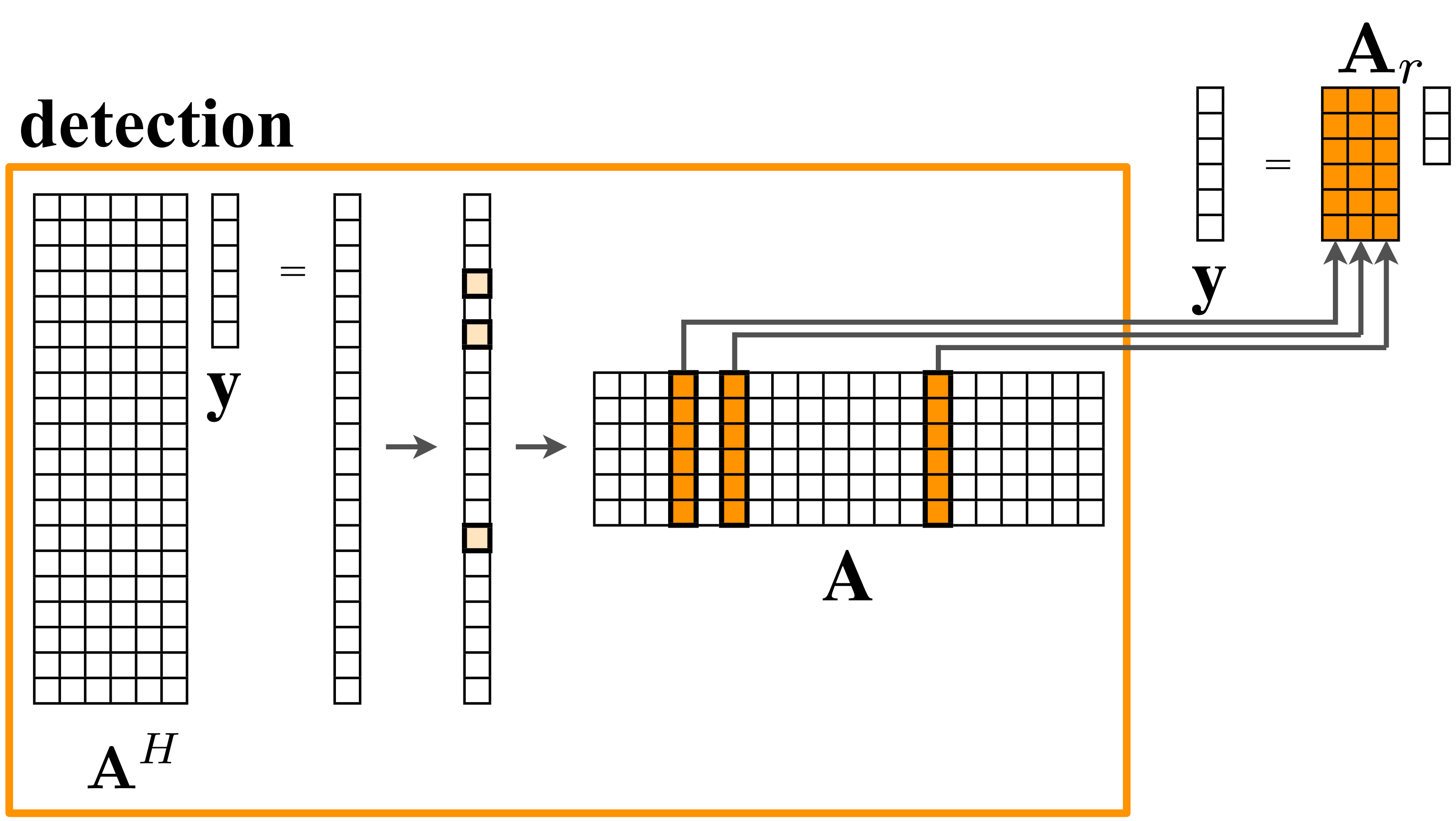


inverse Fourier transform

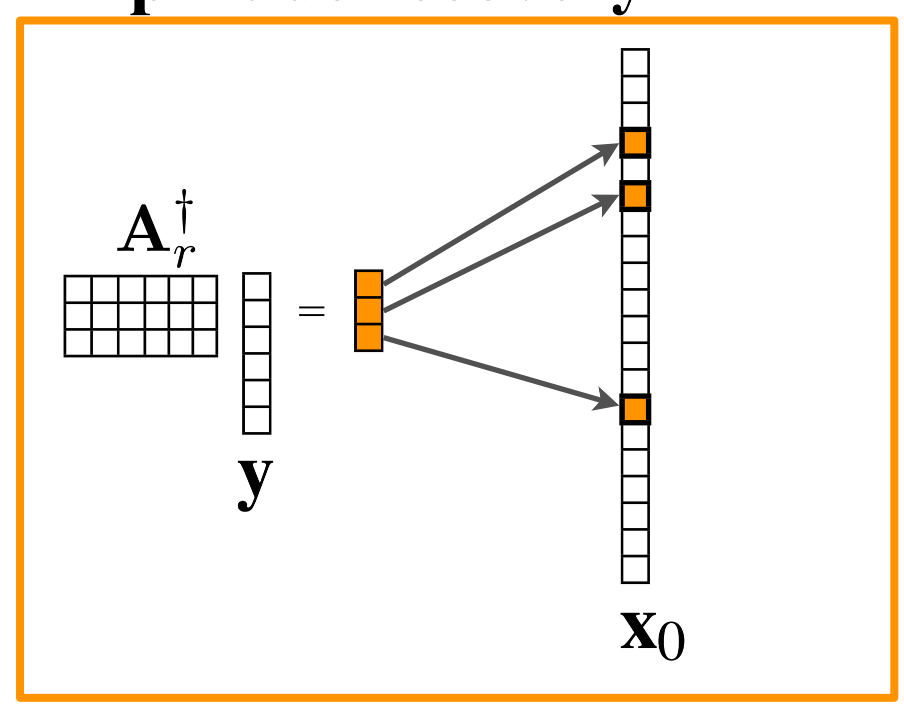
detection + data-consistent amplitude recovery

Fourier transform

detection



data-consistent amplitude recovery



Observations

- 3-fold undersampling
  - random: significant coefficients **detected!**
  - regular: **ambiguity** between significant coefficients and aliases

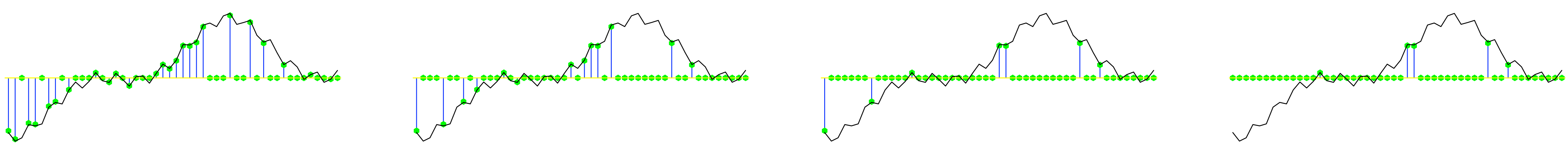
- random undersampling
  - recovery ≈ denoising + amplitudes correction
  - (accurate) recovery of the coefficients above the “noise” level

[Donoho et al ‘06]

Undersampling “noise”

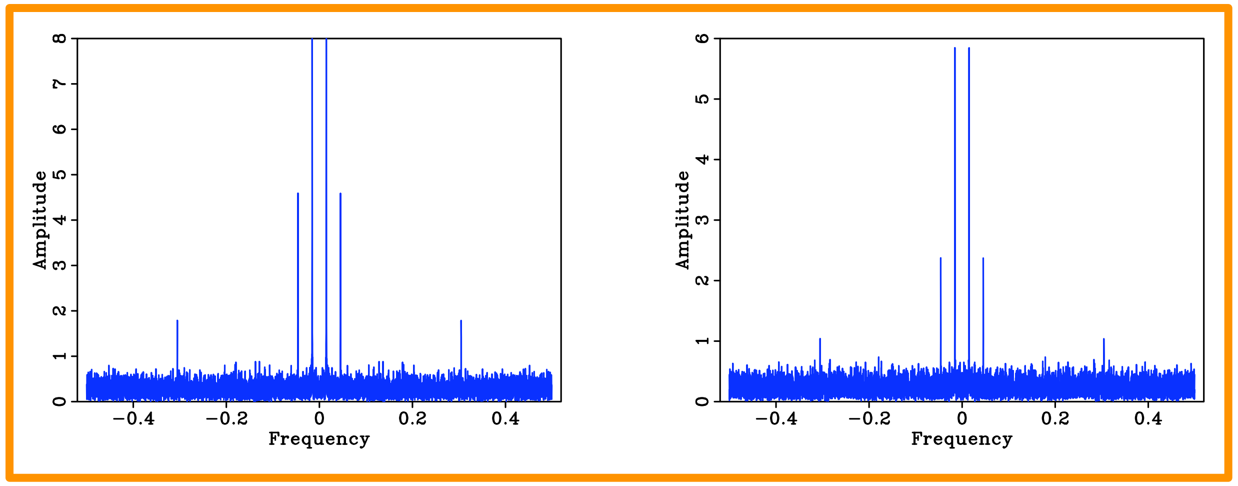
- “noise”
  - due to $\mathbf{A}^H\mathbf{A} \neq \mathbf{I}$
  - defined by $\mathbf{A}^H\mathbf{A}\mathbf{x}_0-\alpha\mathbf{x}_0 = \mathbf{A}^H\mathbf{y}-\alpha\mathbf{x}_0$

1 out of 2 | 1 out of 4 | 1 out of 6 | 1 out of 8

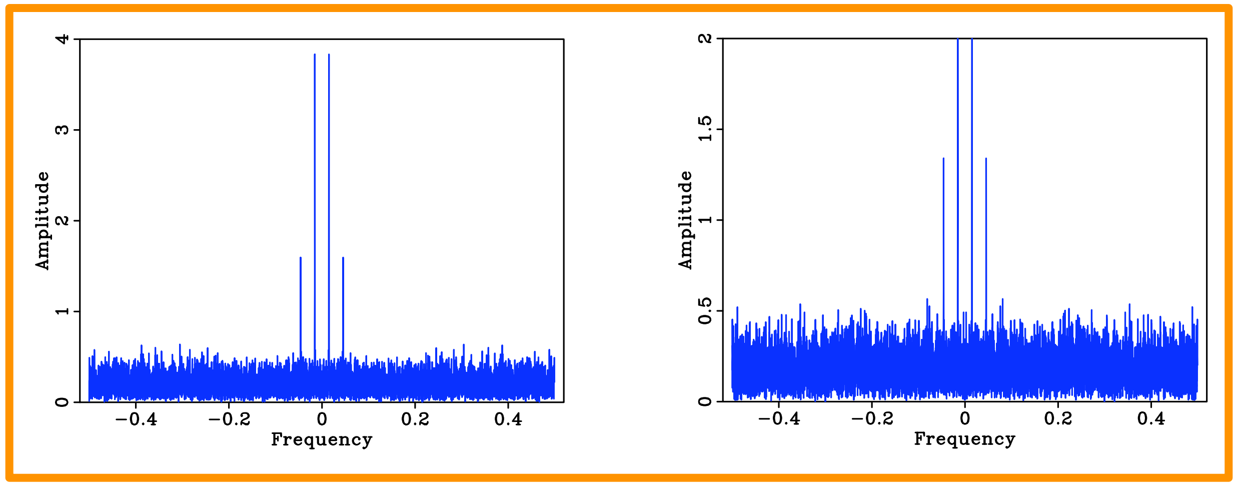


less acquired data

3 detectable Fourier modes



2 detectable Fourier modes

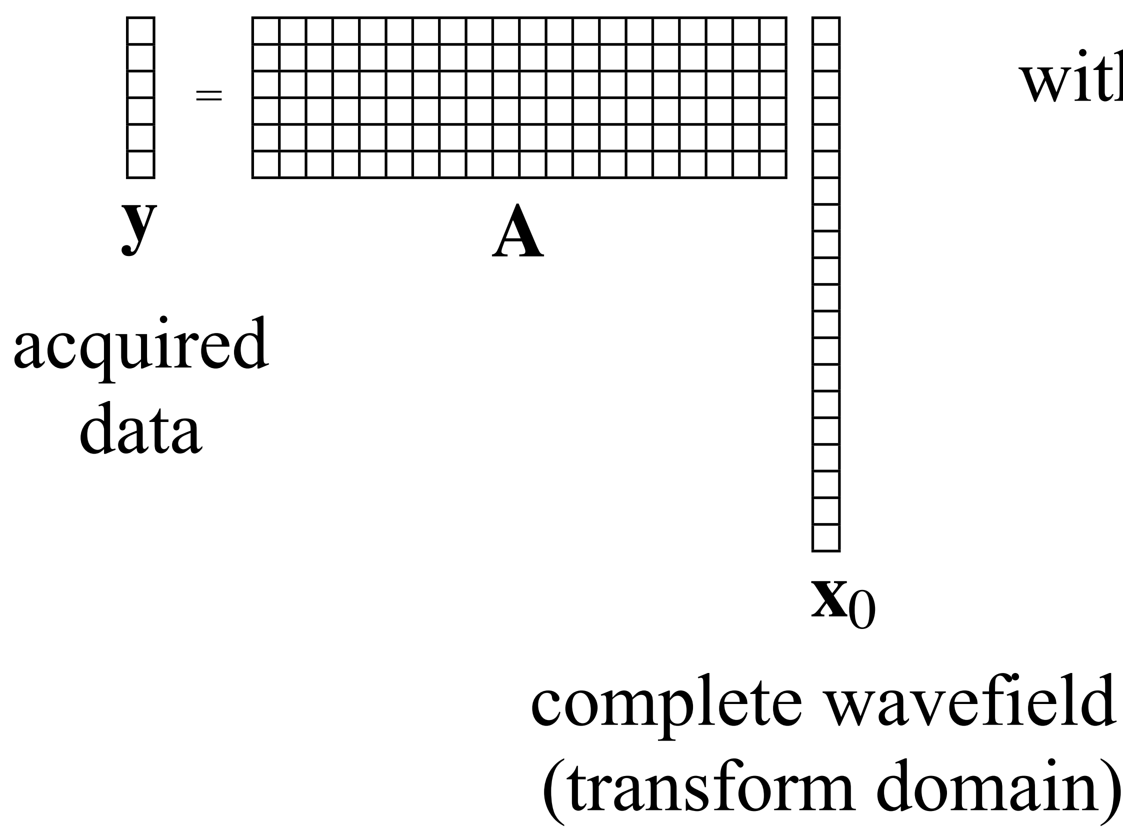


Further observations & comments

- random undersampling
  - size of the undersampling “noise” is a function of the undersampling factor
    - the less data acquired, the higher the “noise” level
  - for increasing undersampling
    - the largest coefficients remain detectable for the longest
  - for given undersampling
    - fixed number of recoverable coefficients
    - the more energy these significant coefficients carry compared to the total energy, the better the recovery ⇒ **need of an efficient representation for seismic data**

[Candès et al ‘05]
[Donoho ‘06]

Sparsity-promoting wavefield reconstruction



restriction operator

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

sparsifying transform for seismic data

Interpolated data given by $\tilde{\mathbf{f}} = \mathbf{S}^H\tilde{\mathbf{x}}$ with

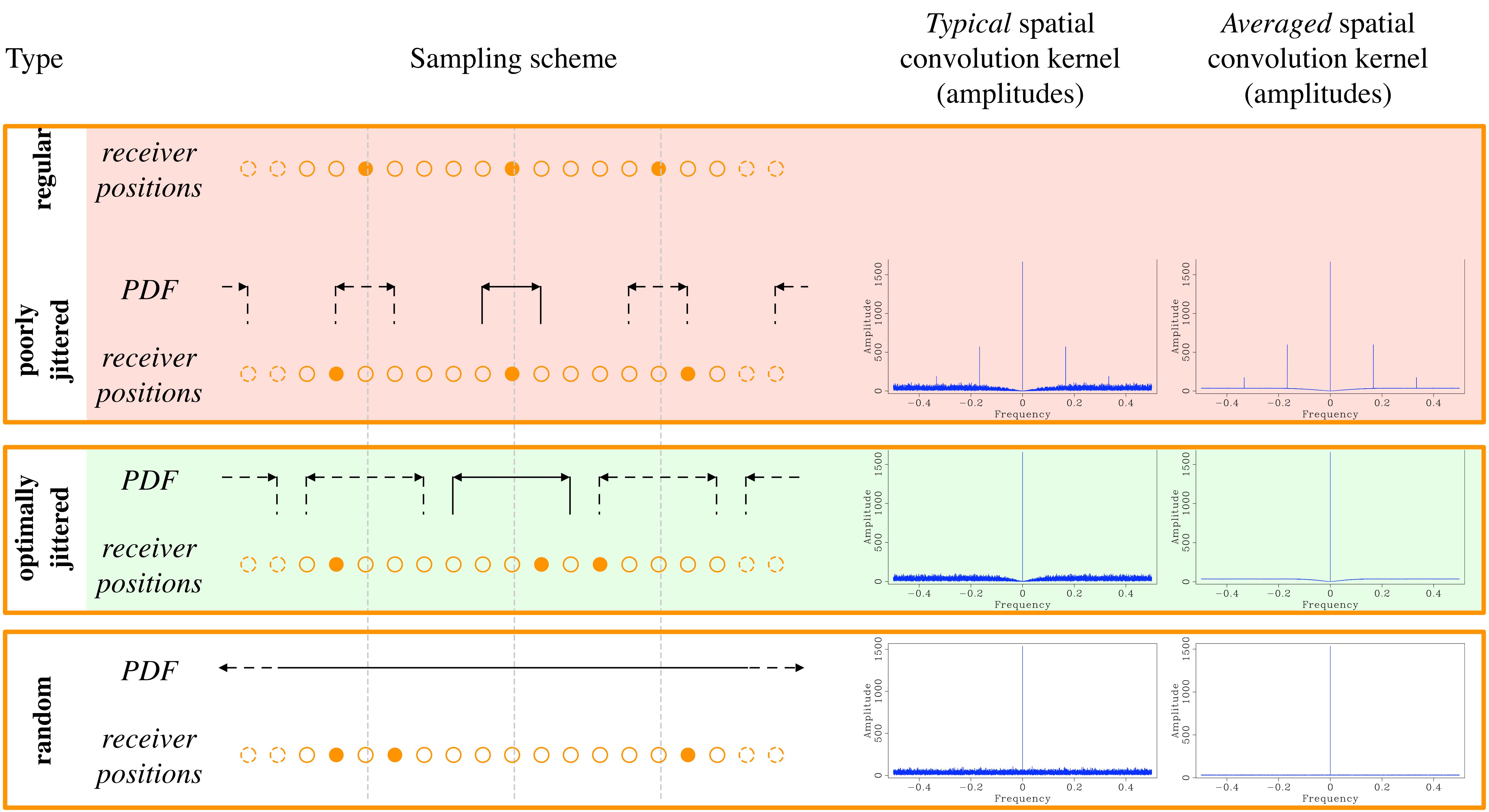
$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} ||\mathbf{x}||_1 \quad \text{s.t.} \quad \mathbf{y} = \mathbf{A}\mathbf{x}$$

[Sacchi et al ‘98]
[Xu et al ‘05]
[Zwartjes and Sacchi ‘07]
[Herrmann and Hennenfent ‘08]

Nonlinear wavefield sampling

- *sparsifying transform*
  - typically **localized** in the time-space domain to handle the complexity of seismic data
    - curvelet transform (dyadic-parabolic partition of the f-k domain)
    - [windowed Fourier transform]
- *sampling scheme*
  - generates incoherent random undersampling “noise” in the sparsifying domain
  - do not create large gaps
    - because of the limited spatiotemporal extend of transform elements used for the reconstruction
- *sparsity-promoting solver*
  - requires few matrix-vector multiplications

Discrete random jittered undersampling

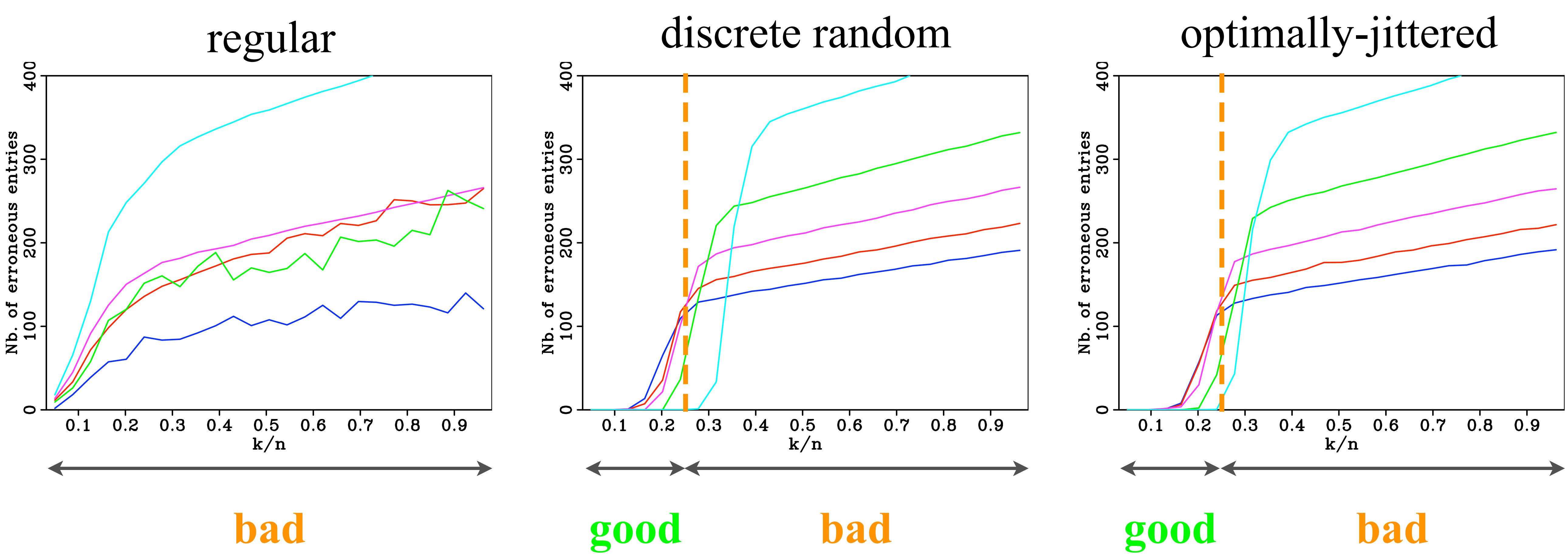


[Hennenfent and Herrmann '08]

Recovery from random vs. opt.-jittered data

- *k*-sparse signal of length *N* in the Fourier domain
- *n* observations in the time domain
  - $n = N/\gamma$ with the undersampling factor γ ranging from 2 to 6

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} ||\mathbf{x}||_1 \quad \text{s.t.} \quad \mathbf{y} = \mathbf{A}\mathbf{x}$$



[Hennenfent and Herrmann '08]

Curvelet Recovery w Sparsity-promoting Inversion

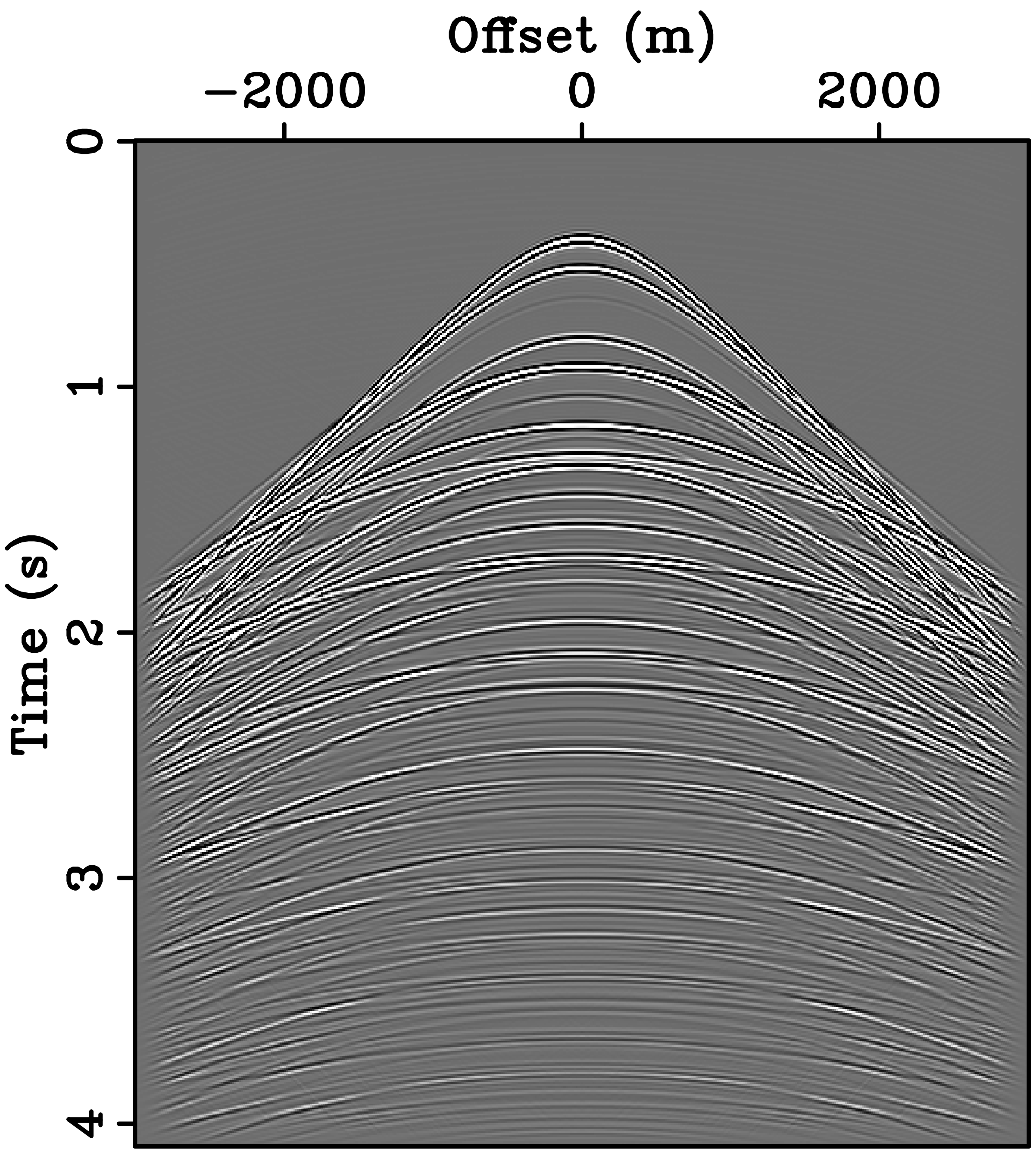
- Interpolated data given by $\tilde{\mathbf{f}} = \mathbf{C}^H \tilde{\mathbf{x}}$ with

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \mathbf{y} = \mathbf{R}\mathbf{C}^H \mathbf{x}$$

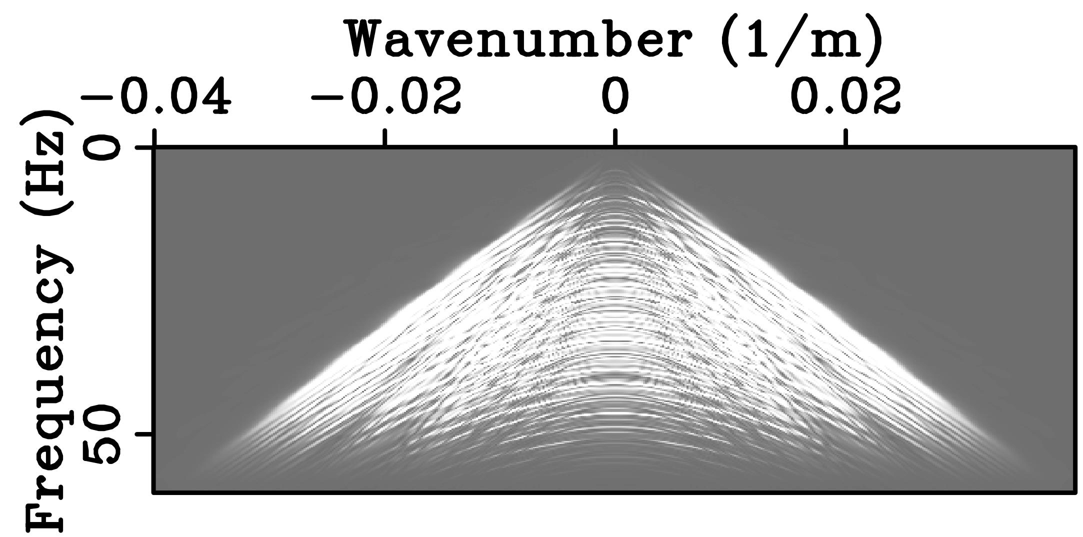
- sparsity-promoting solver
  - Iterative Soft Thresholding with cooling (ISTc)

[Herrmann and Hennenfent ‘08]

Model

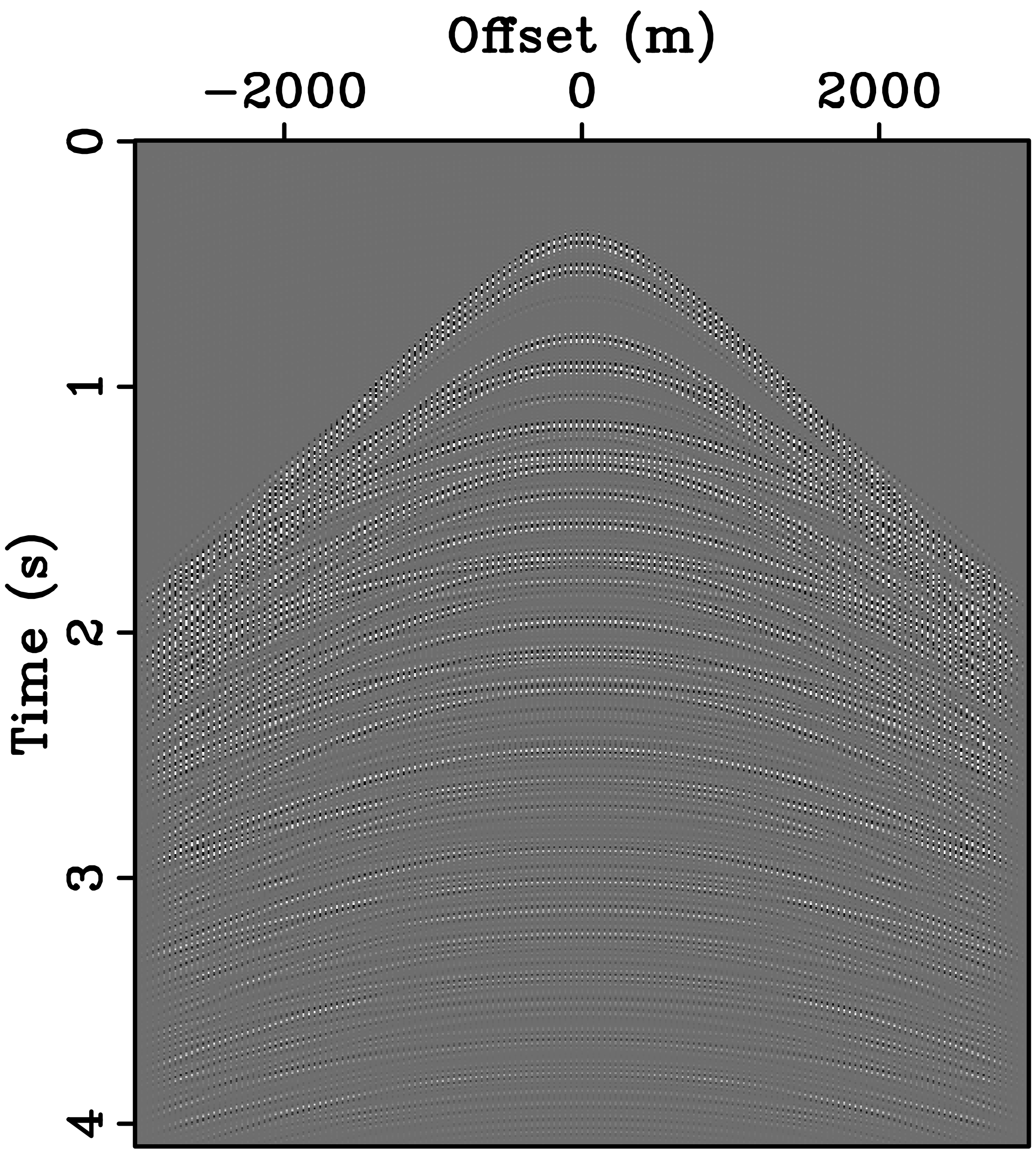


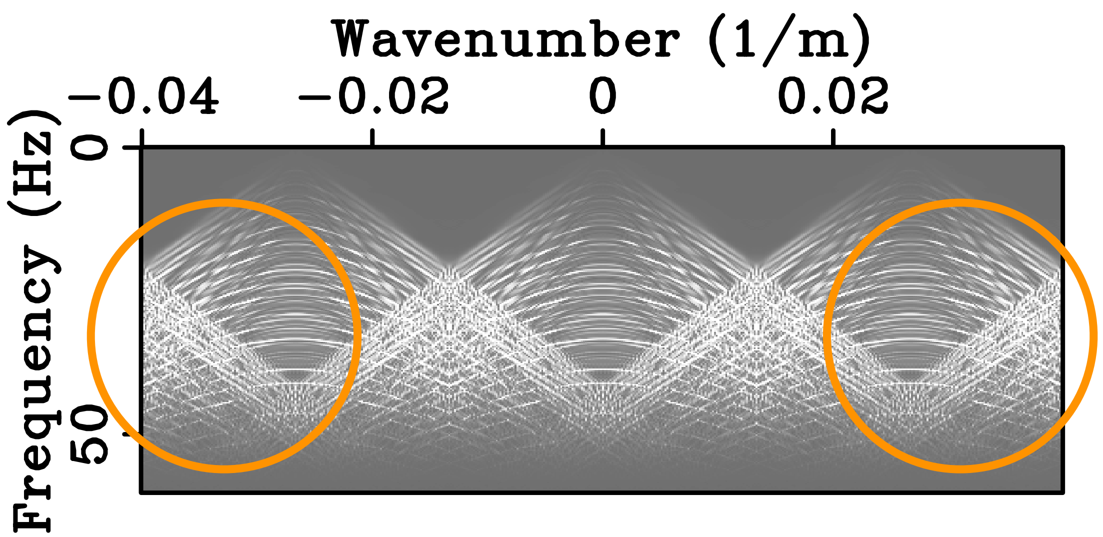
Offset (m)
−2000
0
2000
Time (s)
0
1
2
3
4



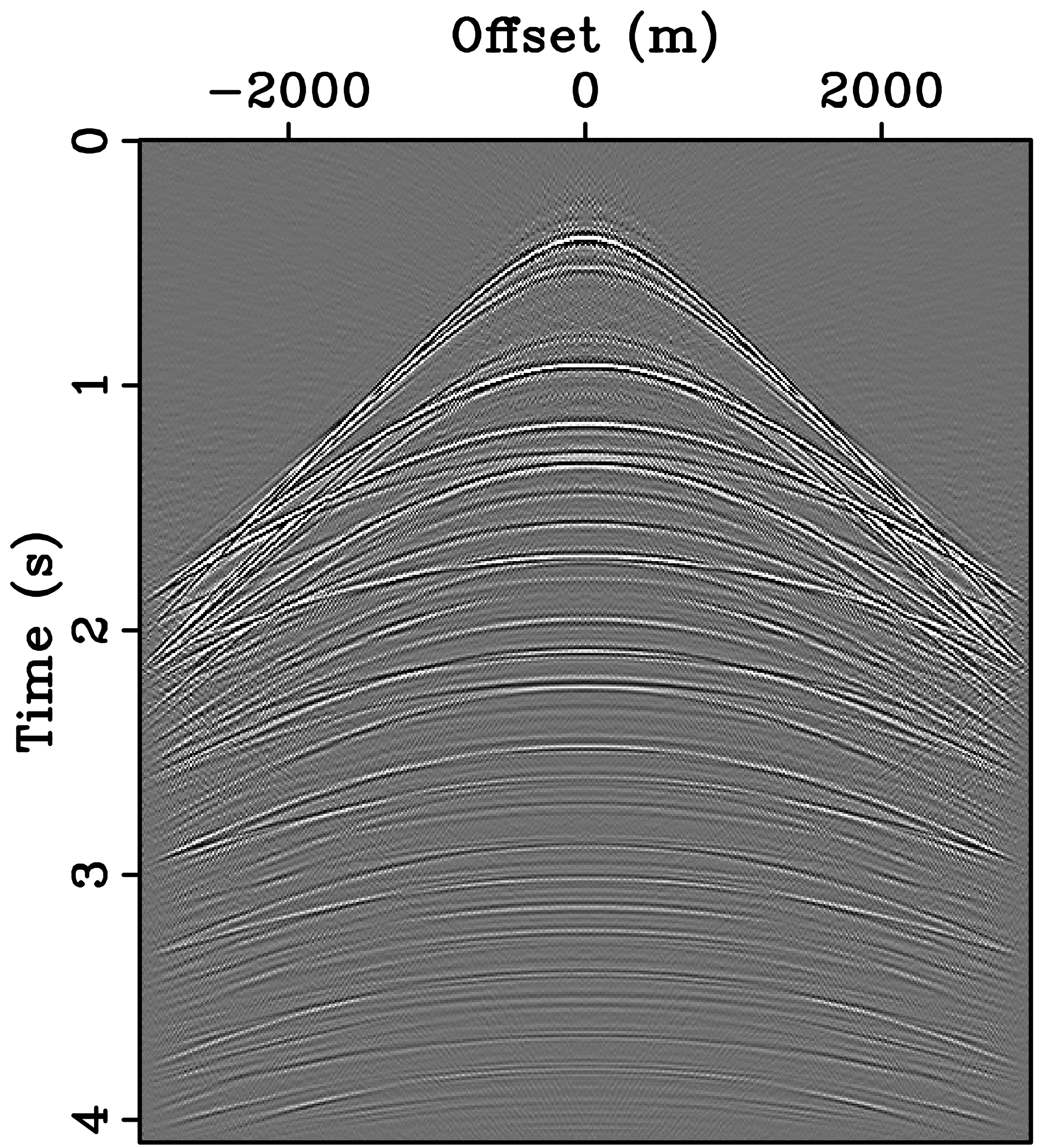
Wavenumber (1/m)
−0.04
−0.02
0
0.02
Frequency (Hz)
0
50

Regular 3-fold undersampling

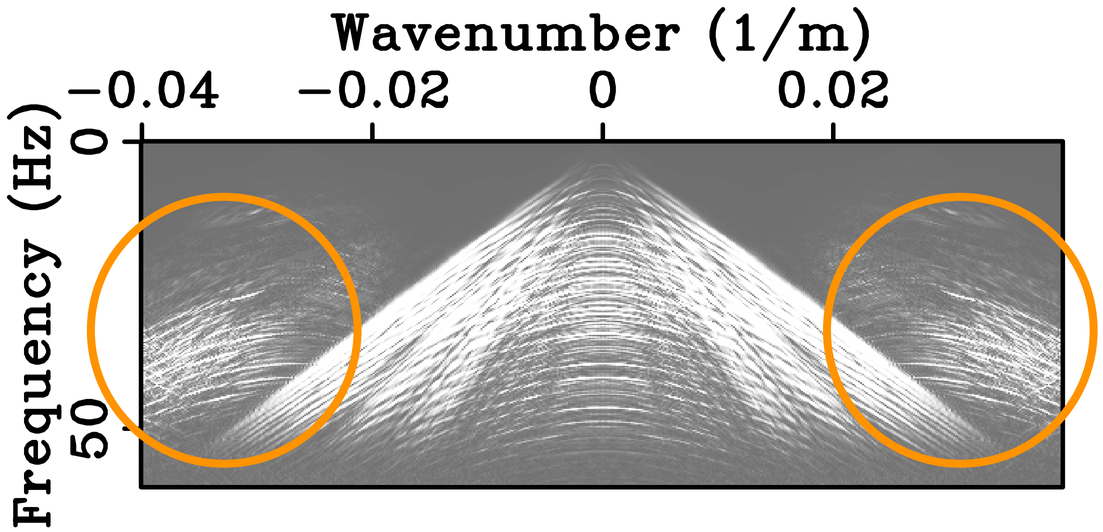




CRSI from regular 3-fold undersampling

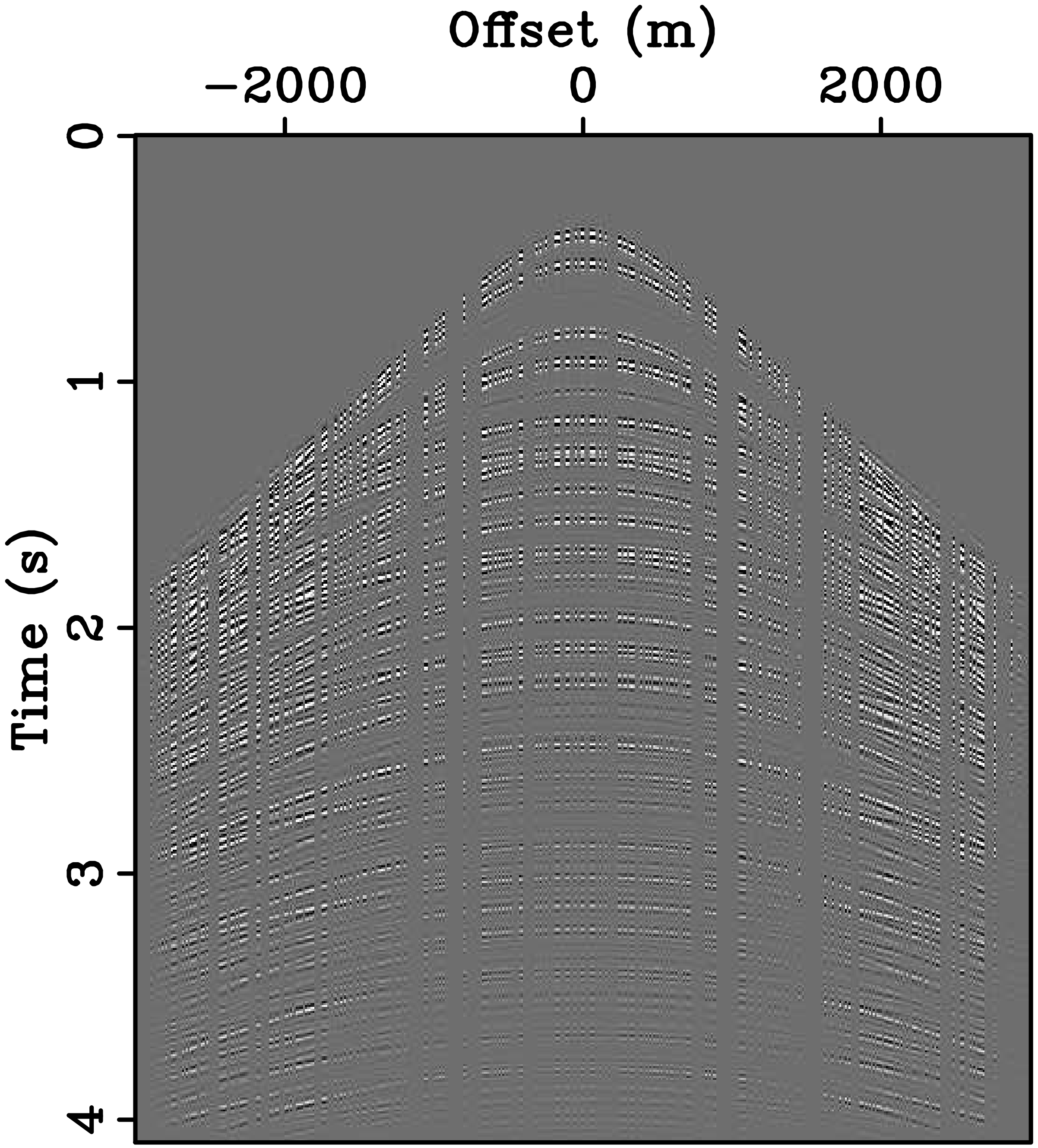


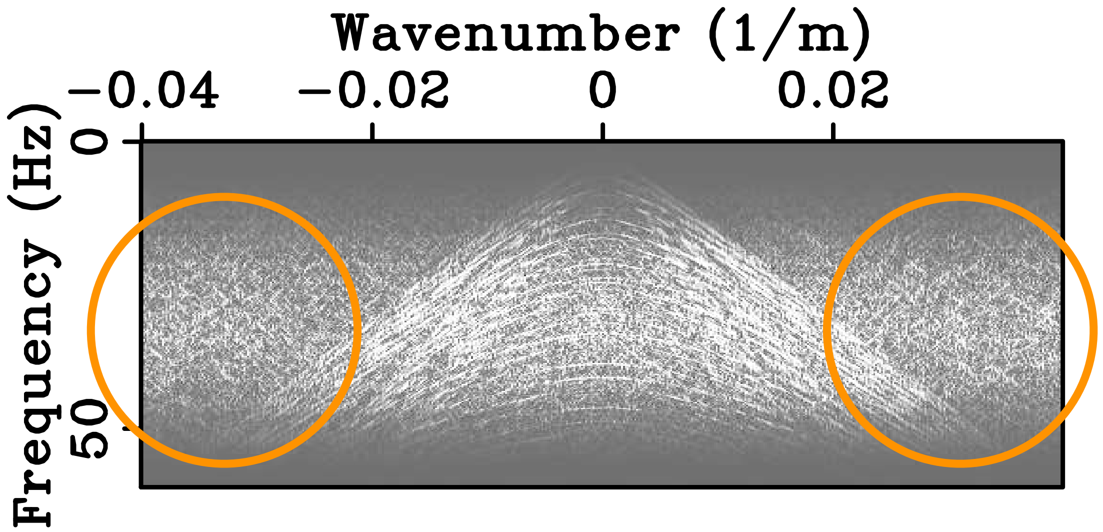
SNR = 6.92 dB



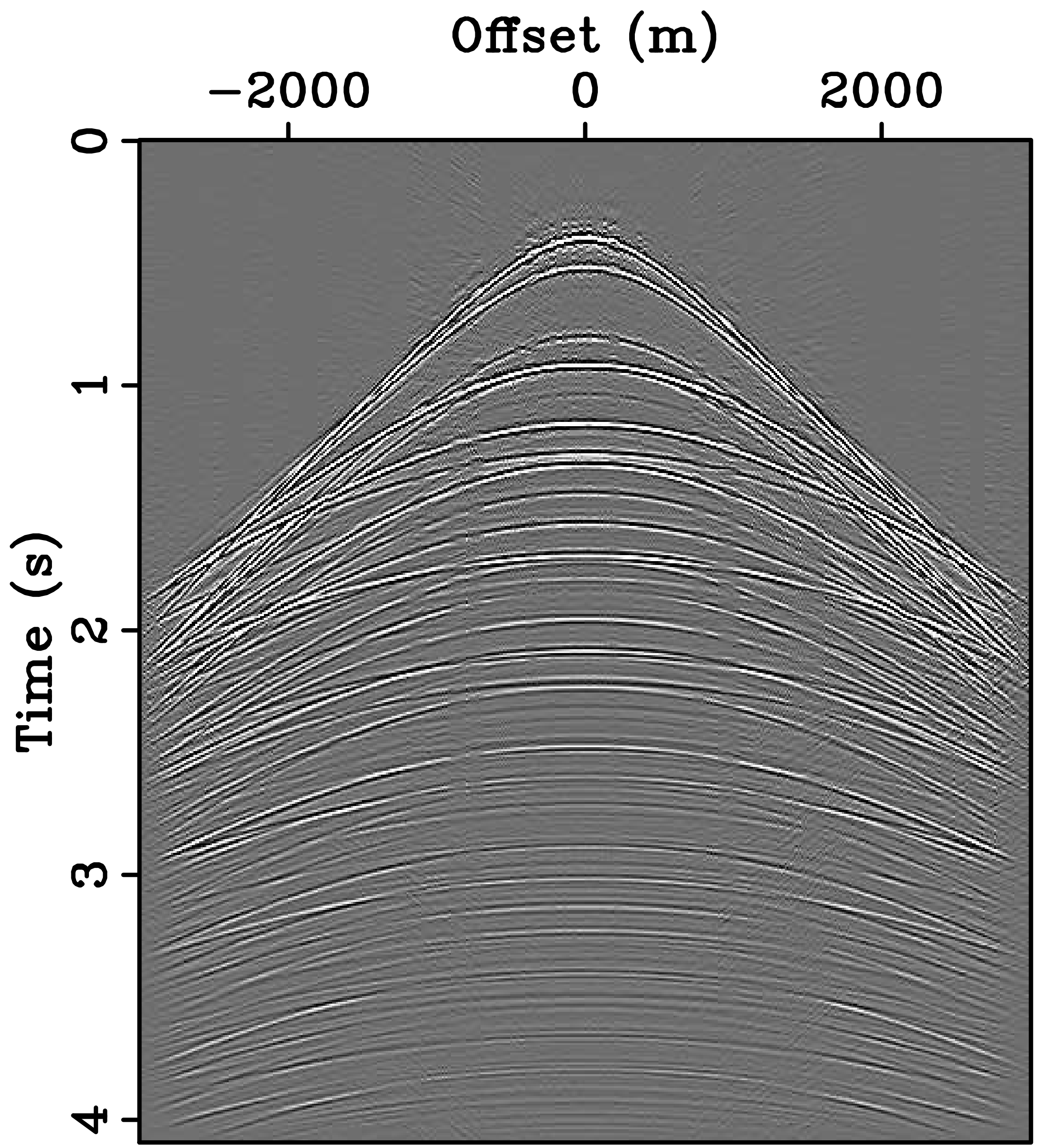
$$\text{SNR} = 20 \times \log_{10}\left(\frac{\|\text{model}\|_2}{\|\text{reconstruction error}\|_2}\right)$$

Random 3-fold undersampling

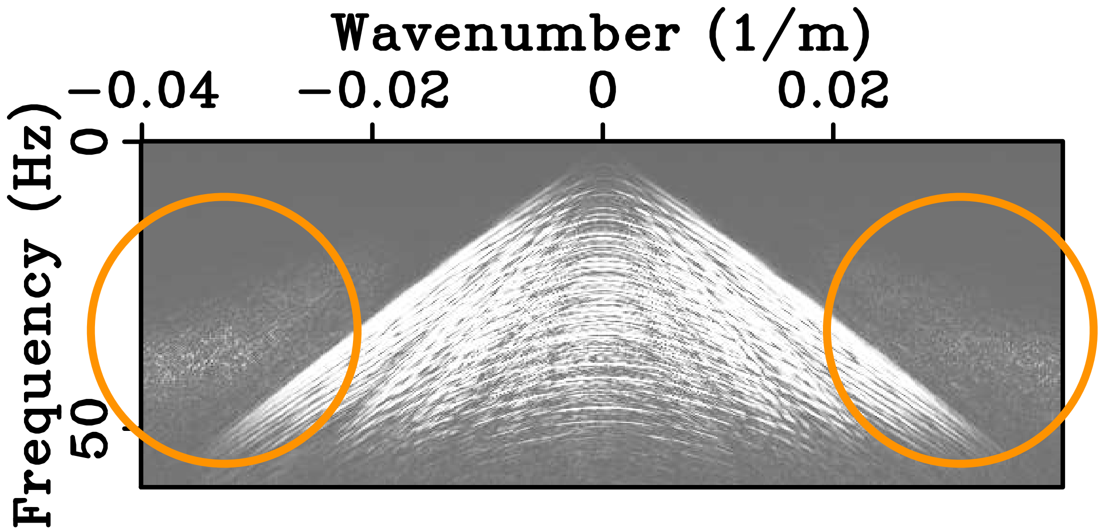




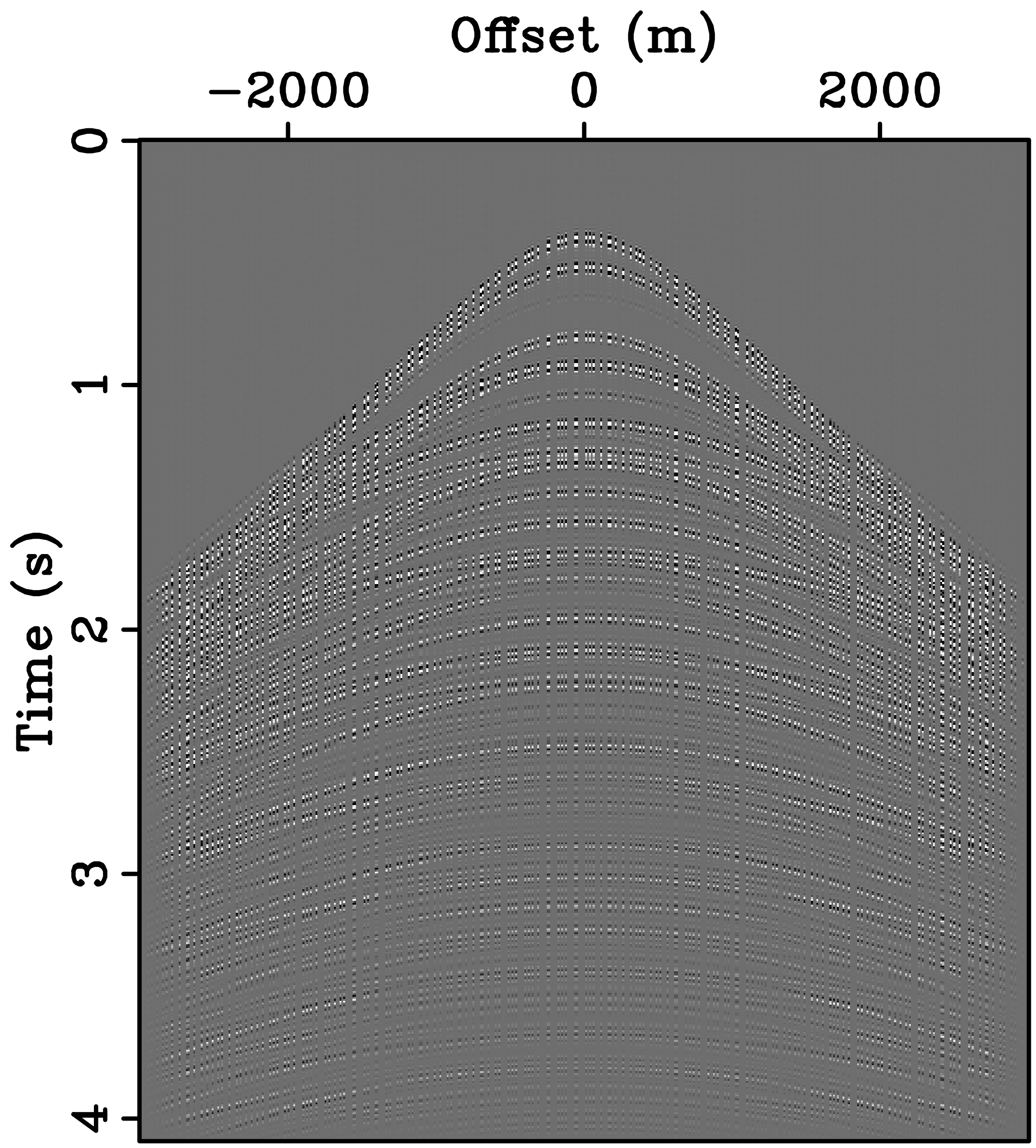
CRSI from random 3-fold undersampling

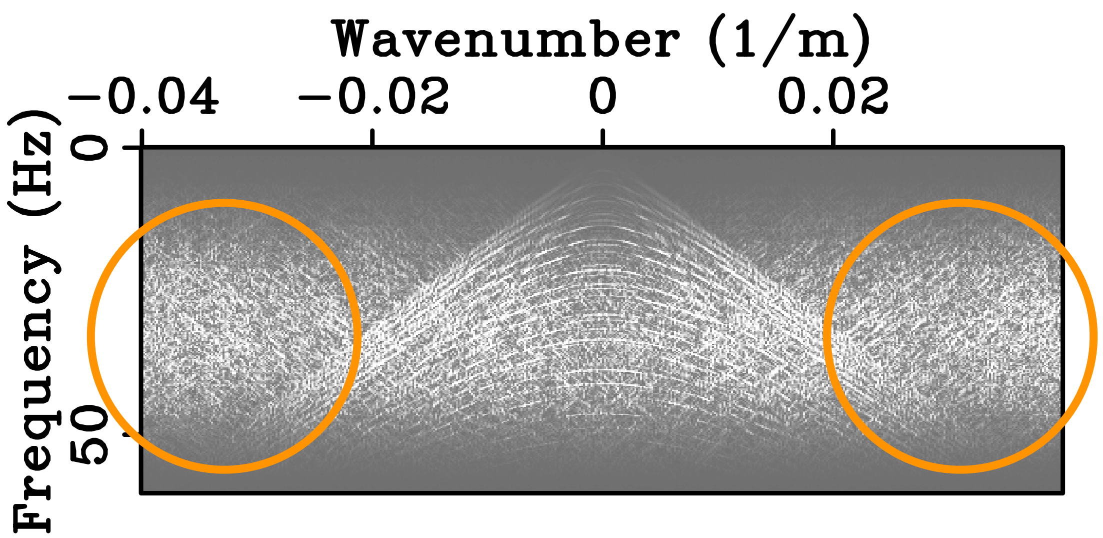


SNR = 9.72 dB

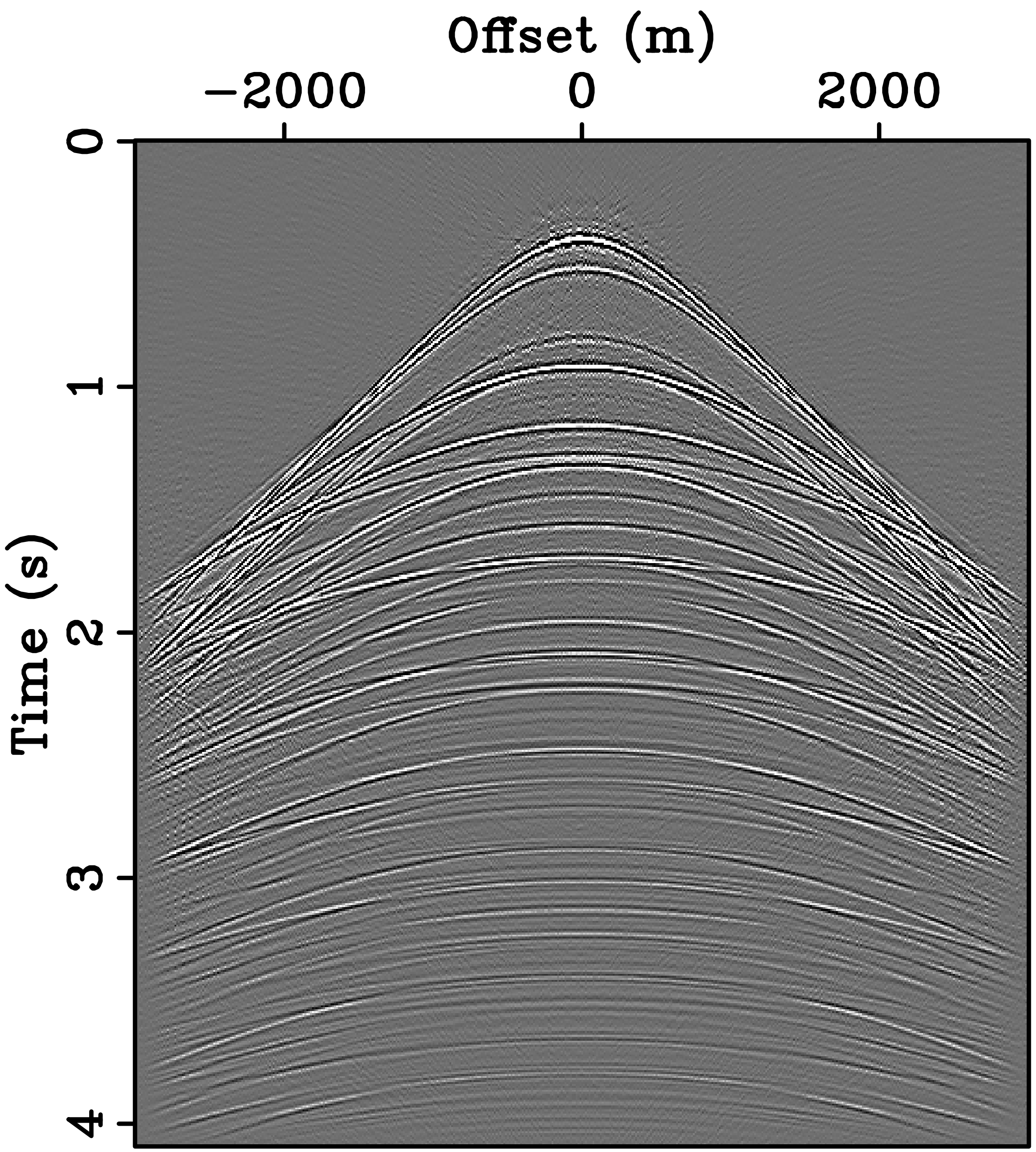


Optimally-jittered 3-fold undersampling

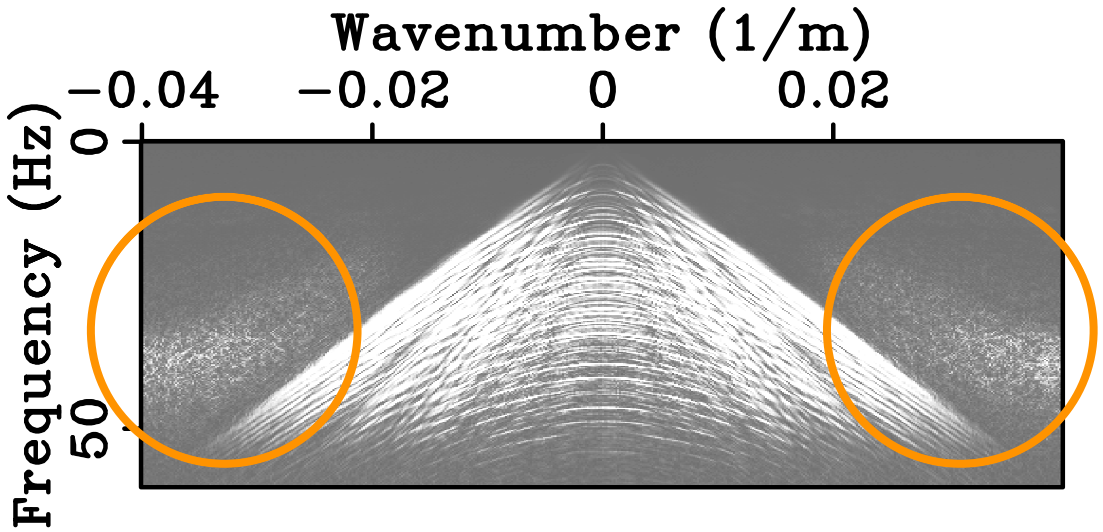




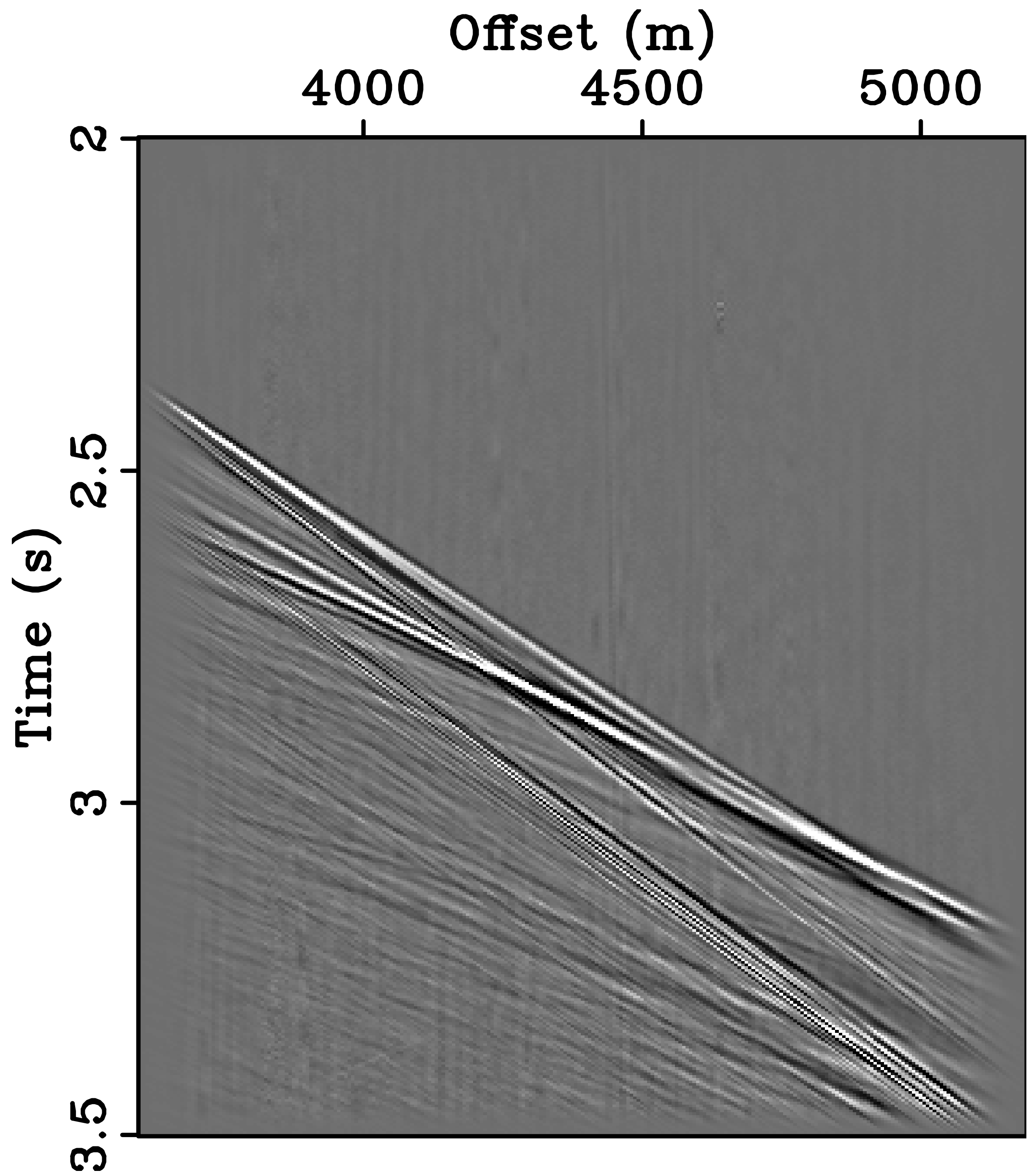
CRSI from opt.-jittered 3-fold undersampling



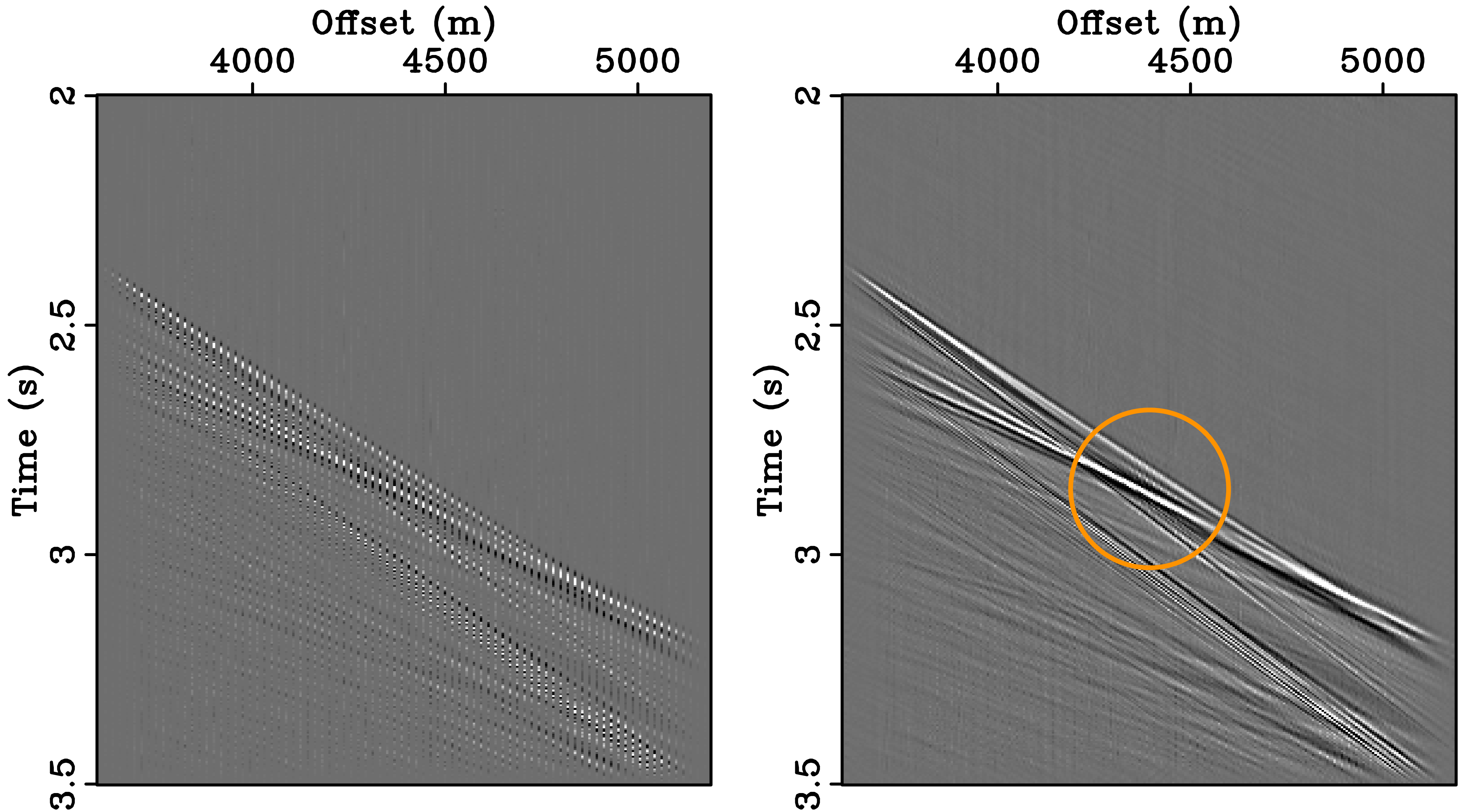
SNR = 10.42 dB



Model

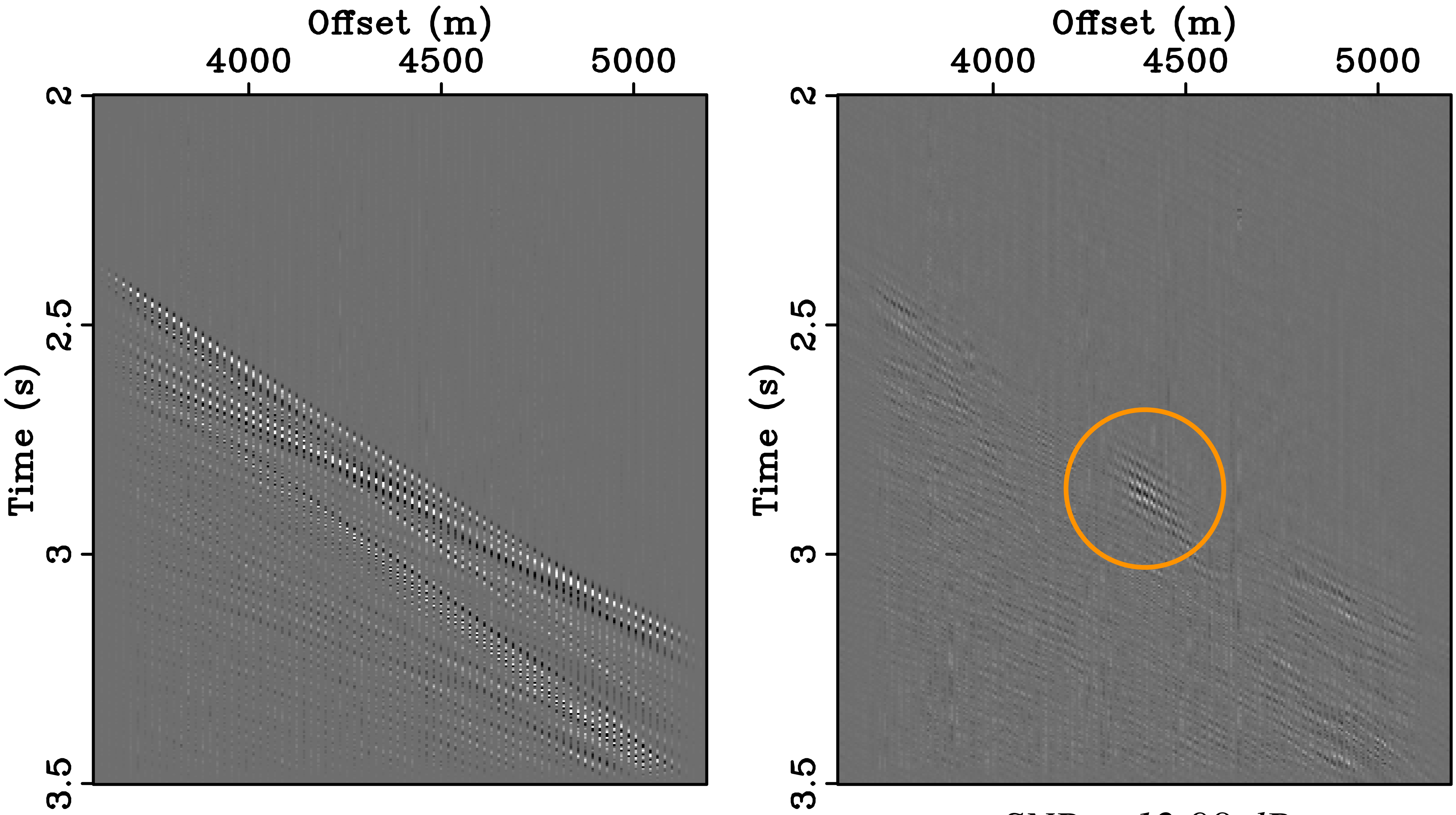


Regular 3-fold undersampling



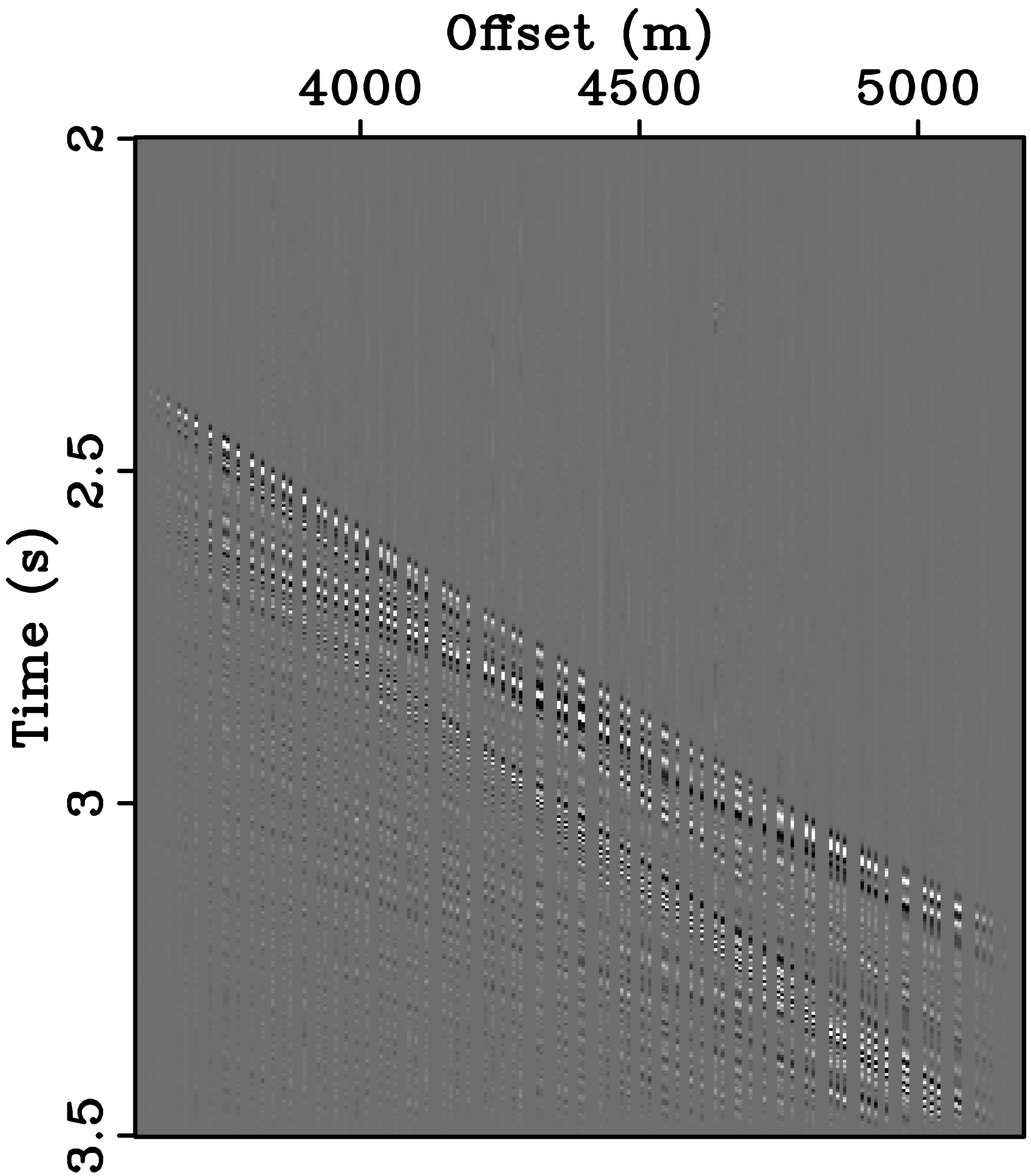
SNR = 12.98 dB

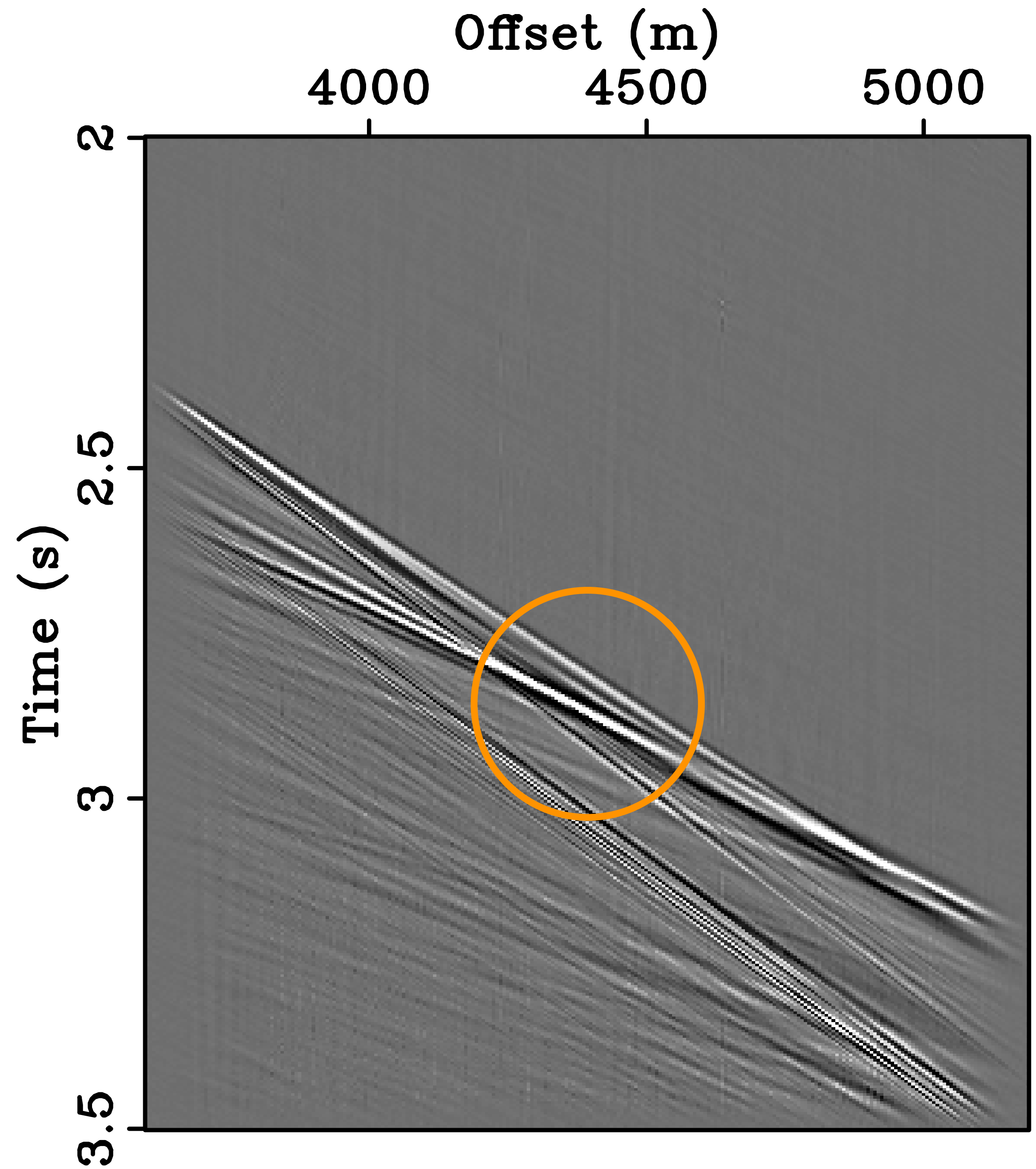
Regular 3-fold undersampling



SNR = 12.98 dB

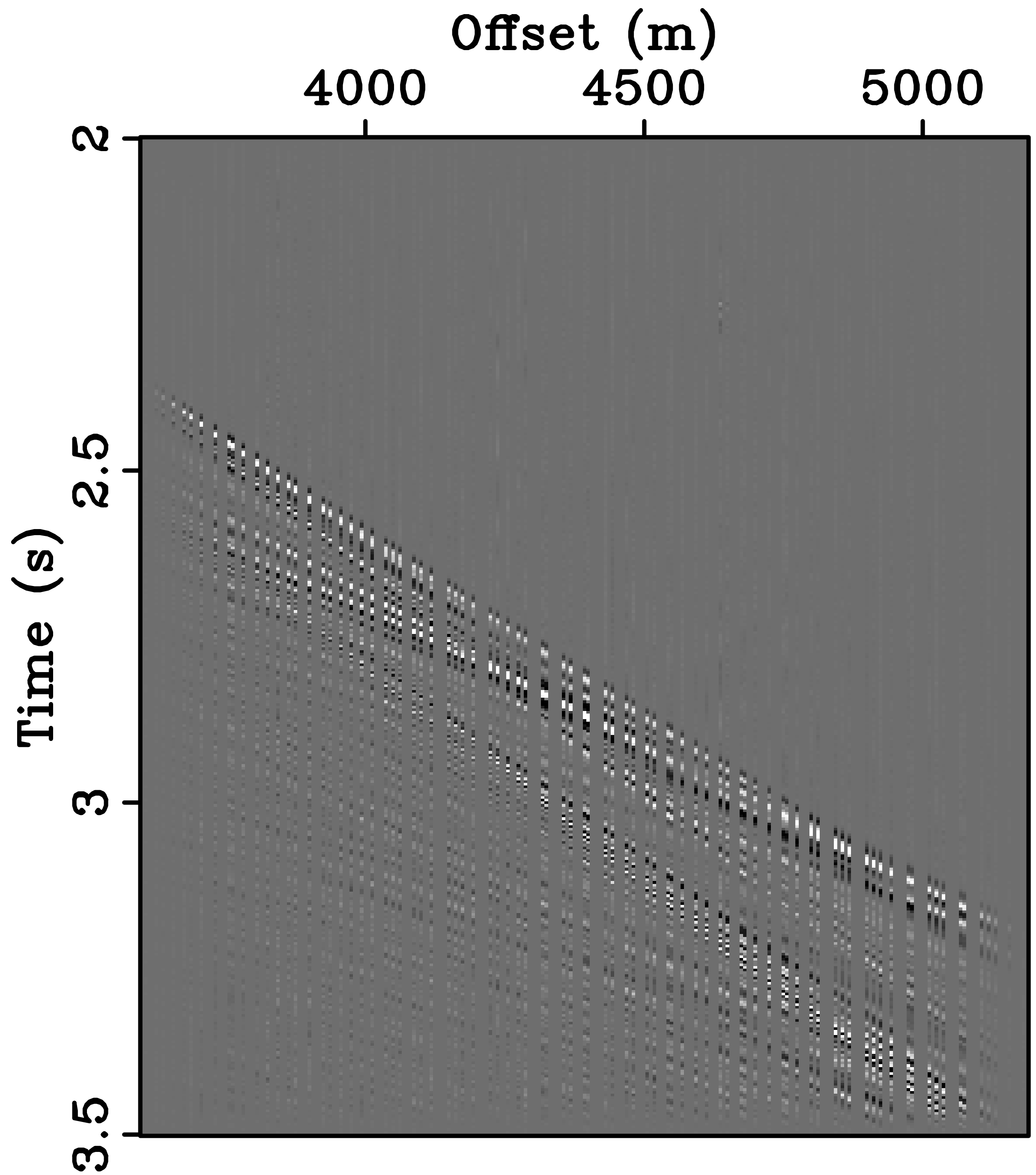
Optimally-jittered 3-fold undersampling

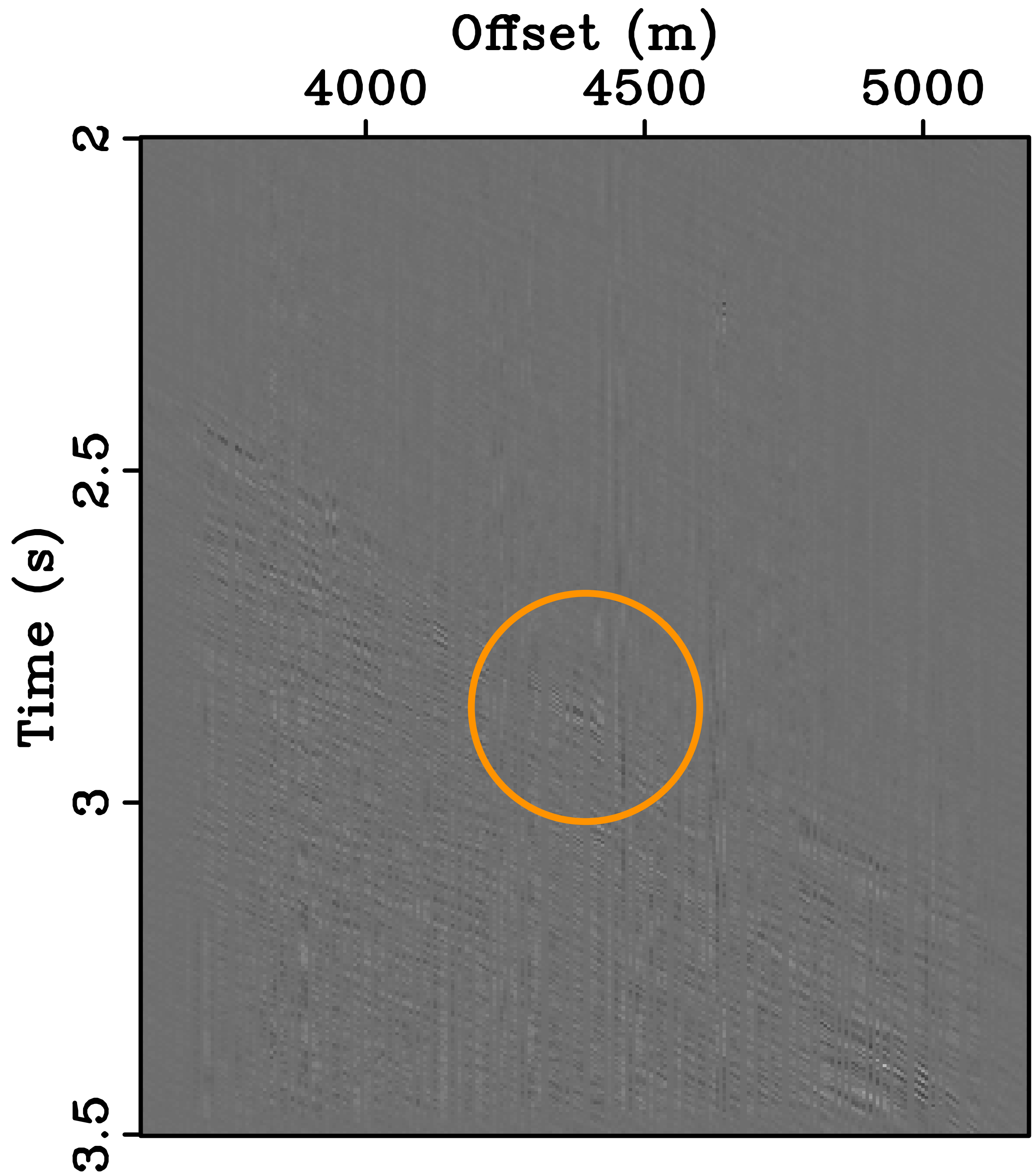




SNR = 15.22 dB

Optimally-jittered 3-fold undersampling

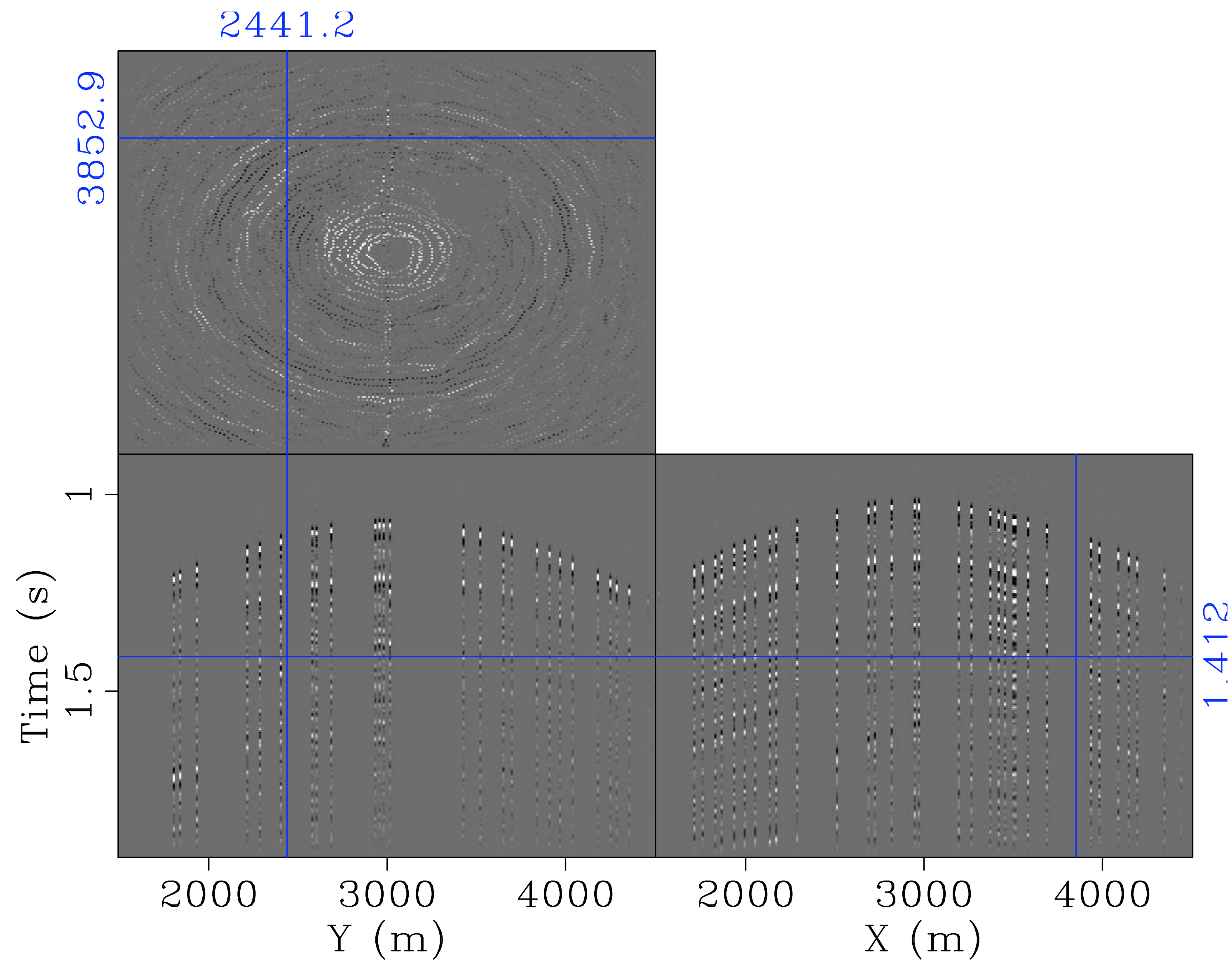




SNR = 15.22 dB

Is jittered undersampling practical?

- field data
  - typ. irregularly sampled
  - no large gaps when possible



Conclusions

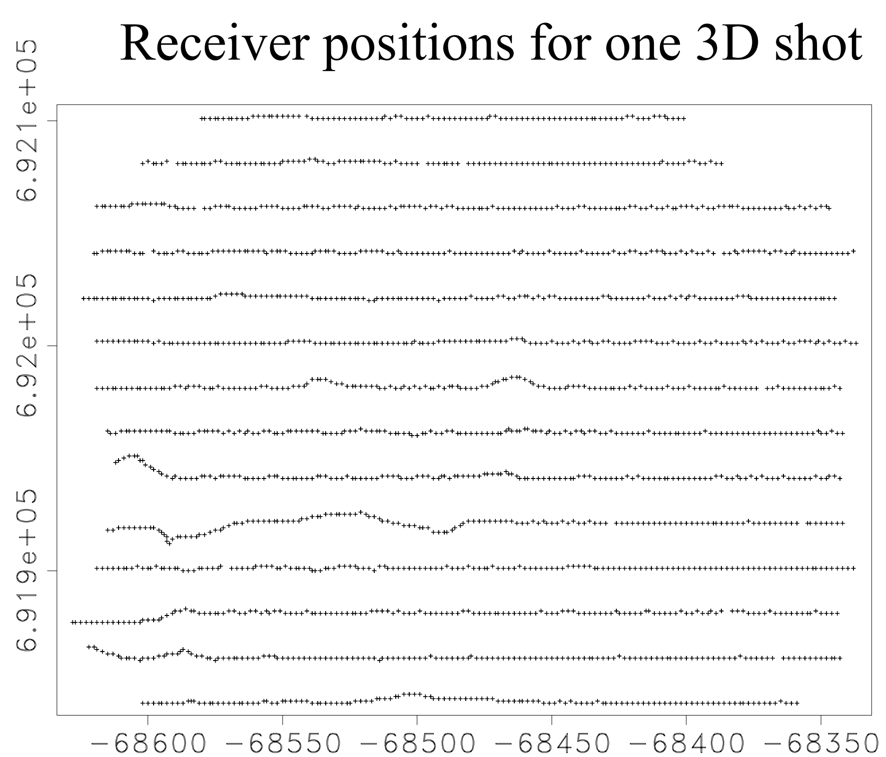
- *sparsity* is a powerful property that offers striking benefits for signal reconstruction BUT it is not enough

- in the sparsifying domain, *interpolation is a denoising problem*
  - regular undersampling:
    harmful coherent undersampling "noise", i.e., aliases
  - random & optimally-jittered undersamplings:
    harmless incoherent random undersampling "noise"

- nonlinear wavefield sampling
  - sparsifying transform: **curvelet transform**
  - coarse sampling scheme: **optimally-jittered undersampling**
  - sparsity-promoting solver: **iterative soft thresholding with cooling**

Future work

- translate jittered undersampling into **practical** acquisition geometries
  - 2D
    - regular receiver positions, jittered source positions?
  - 3D
    - jittered receiver lines, jittered source positions?



- work on **deterministic AND practical** undersampling schemes

Future work

- translate jittered undersampling into **practical** acquisition geometries
  - 2D
    - regular receiver positions, jittered source positions?
  - 3D
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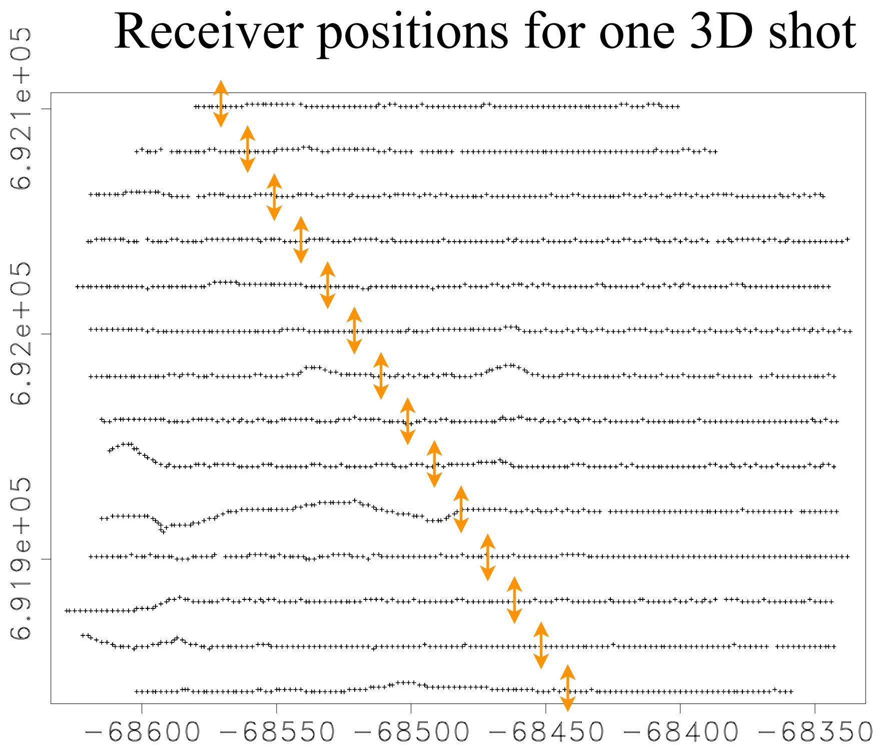


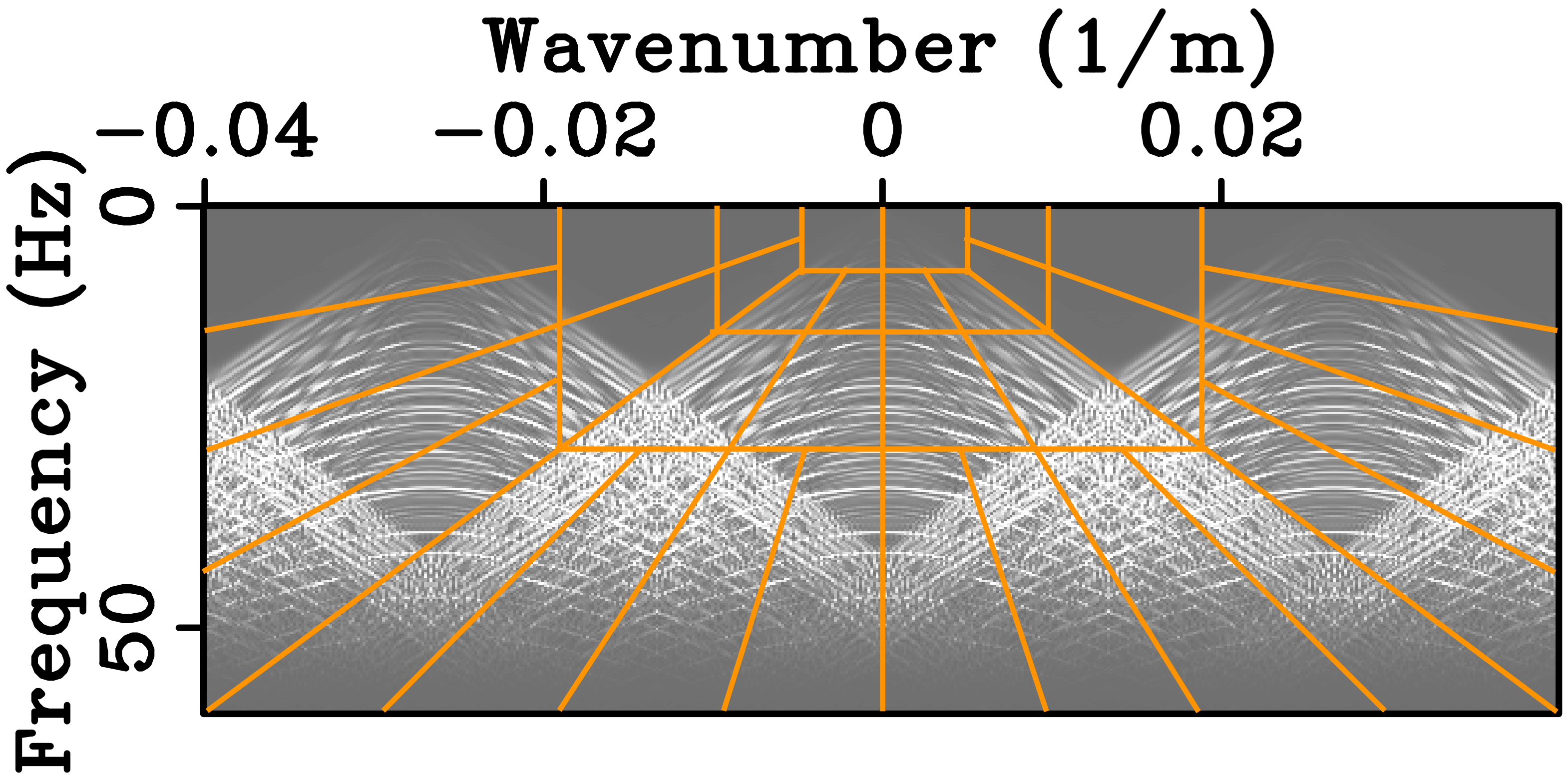
- work on **deterministic AND practical** undersampling schemes

More future work

- CRSI & regular undersampling
  - explore neighbourhood in phase-space to break aliasing

data misfit — **sparsity** — **smooth neighbourhood**

$$\min_{\mathbf{x}} \frac{1}{2}\|\mathbf{y} - \mathbf{R}\mathbf{C}^H\mathbf{x}\|_2^2 + \lambda_1\|\mathbf{x}\|_1 + \lambda_2\|\mathbf{L}\mathbf{x}\|_2$$



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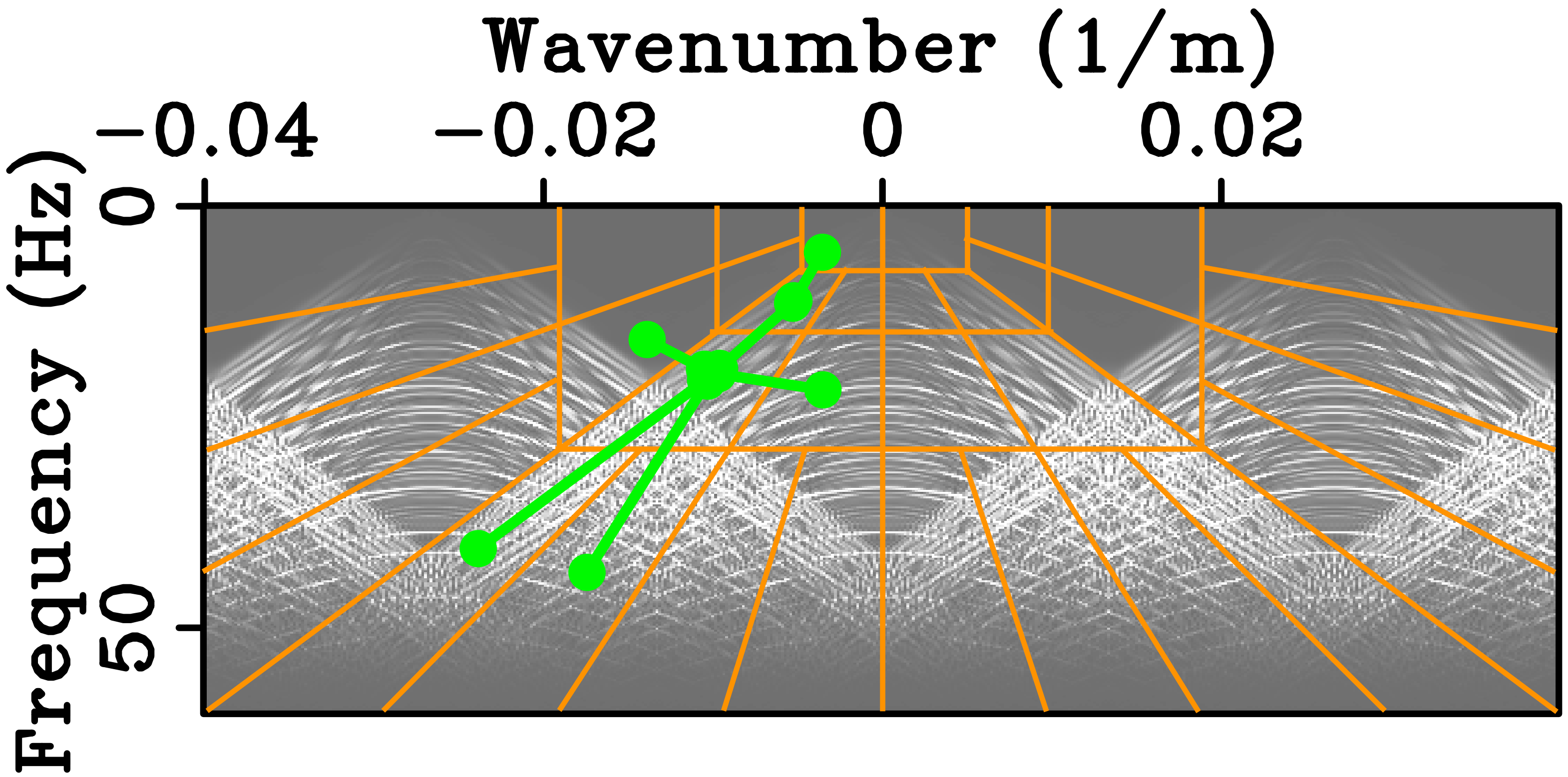

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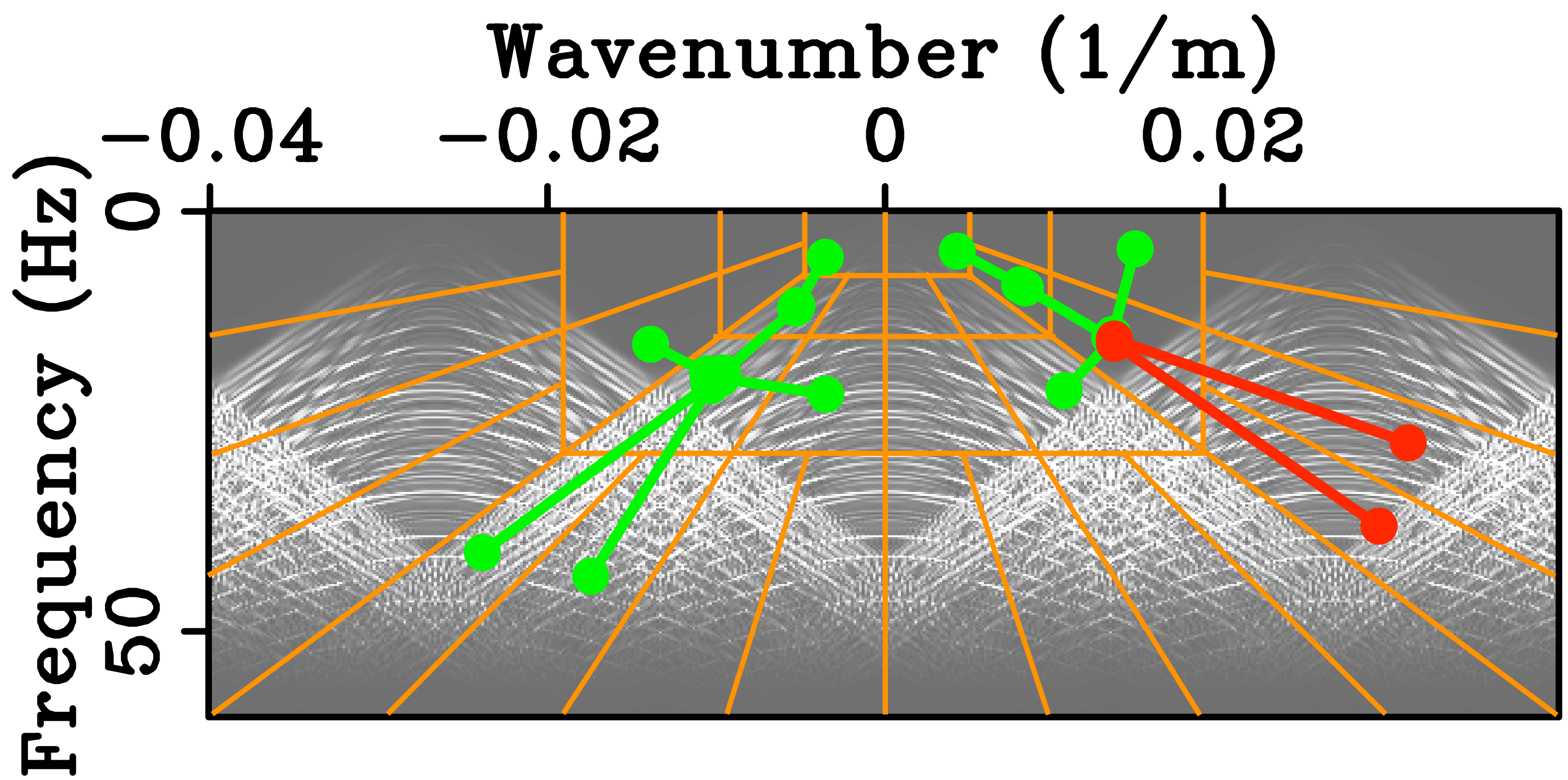

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