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# *Compressed-sensing based land acquisition design*

*Felix J. Herrmann*

# Compressed-sensing based land acquisition design

Rajiv Kumar, Shashin Sharan, Nick Moldoveanu, and Felix J. Herrmann




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Georgia Institute of Technology

Howe, D., Foster, M., Allen, T., Taylor, B. and Jack, I. [2008] Independent simultaneous sweeping -a method to increase the productivity of land seismic crews. 2826–2830.

Lin, T.T. and Herrmann, F.J. [2009] Designing simultaneous acquisitions with compressive sensing. EAGE Annual Conference Proceedings, EAGE, EAGE.

Oristaglio, M. [2012] SEAM Phase II—Land Seismic Challenges. The Leading Edge, 31(3), 264–266.

Mosher, C., Li, C., Williams, L., Carey, T., Olson, R., Malloy, J. and Ji, Y. [2017] Compressive Seismic Imaging: Land Vibroseis operations in Alaska. 127–131.

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# Current acquisition paradigm

Large number of single vibrators to sweep simultaneously

Perform source separation to recover individual shots

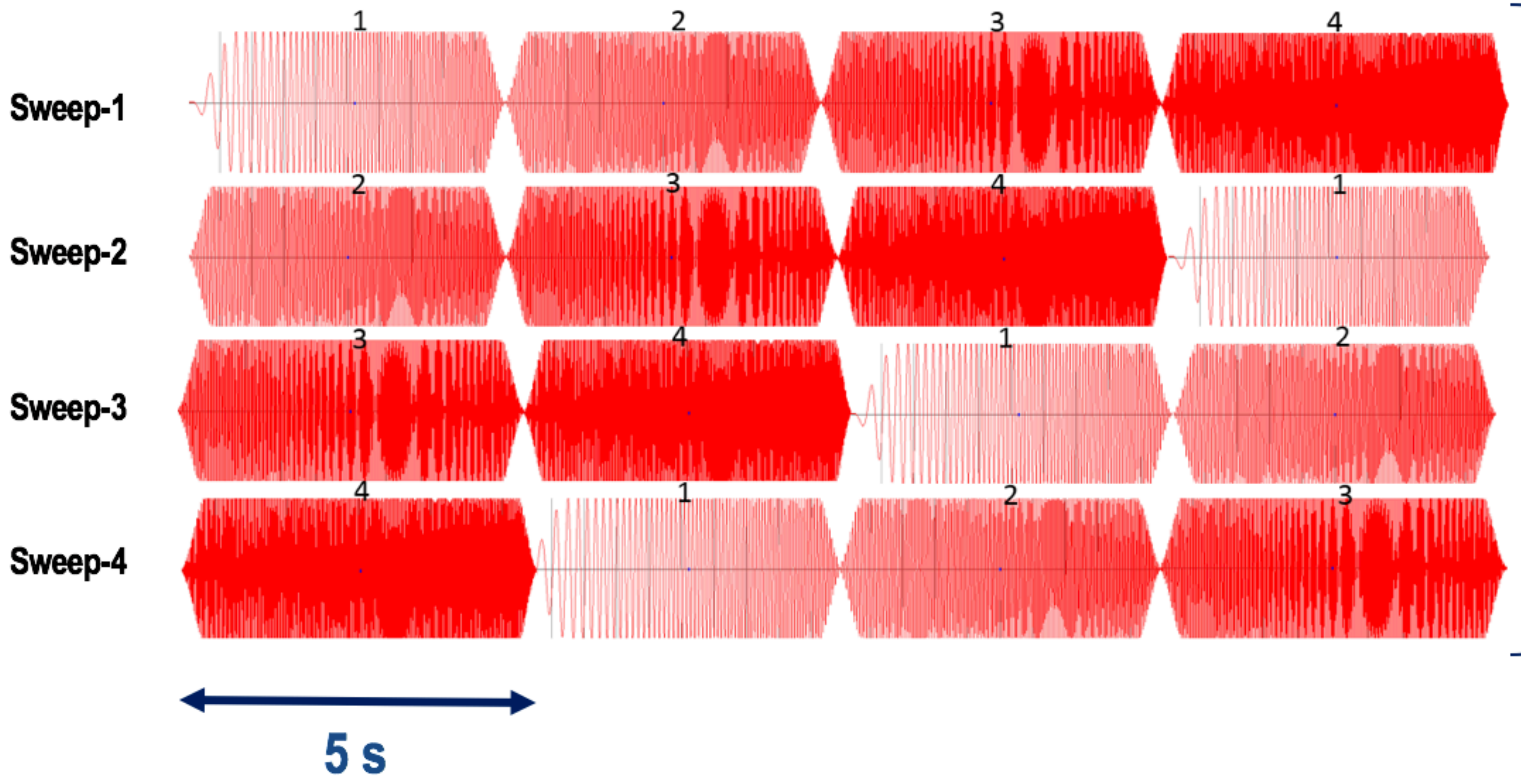
**Cannot be used in the areas with obstruction or permit limitations**

# Phase- and Frequency- encoding


| | | | | | |
|---|---|---|---|---|---|
| **Sweep-1** | 2-28 Hz , phase=0 | 24-48 Hz, phase=90 | 45-69 Hz, phase=180 | 66-90 Hz, phase=270 | 5 sec + 6 sec listen time |
| **Sweep-2** | 24-48 Hz, phase=90 | 45-69 Hz, phase=180 | 66-90 Hz, phase=270 | 2-28 Hz, phase=0 | 5 sec + 6 sec listen time |
| **Sweep-3** | 45-69 Hz, phase=180 | 66-90 Hz, phase=270 | 2-28 Hz, phase=0 | 24-48 Hz, phase=90 | 5 sec + 6 sec listen time |
| **Sweep-4** | 66-90 Hz, phase=270 | 2-28 Hz, phase=0 | 24-48 Hz, phase=90 | 45-69 Hz, phase=180 | 5 sec + 6 sec listen time |

Total time = 44 sec

# Phase- and Frequency- encoding




5 s each + 6s listening
44s non-concatenated
104s conventional

Can we further reduce the acquisition time?

# Motivation

Lower the acquisition cost using simultaneous encoded sweeps

Reduce the sweeping time

Coarsely sampled data w/ insights from Compressive Sensing

Felix J. Herrmann, Michael P. Friedlander, and Ozgur Yilmaz, "**Fighting the Curse of Dimensionality: Compressive Sensing in Exploration Seismology**", *Signal Processing Magazine, IEEE*, vol. 29, p. 88-100, 2012.
Felix J. Herrmann, "**Randomized sampling and sparsity: Getting more information from fewer samples**", *Geophysics*, vol. 75, p. WB173-WB187, 2010.
Gilles Hennenfent and Felix J. Herrmann, "Simply denoise: wavefield reconstruction via jittered undersampling", Geophysics, vol. 73, p. V19-V28, 2008.
Felix J. Herrmann and Gilles Hennenfent, "Non-parametric seismic data recovery with curvelet frames", Geophysical Journal International, vol. 173, p. 233-248, 2008.



# Compressive sensing paradigm

**Sample to break structure = renders interference into incoherent noise**

- randomized acquisition (e.g., time-jittered, over/under, continuous recording etc.)
- destroys sparsity/low rank

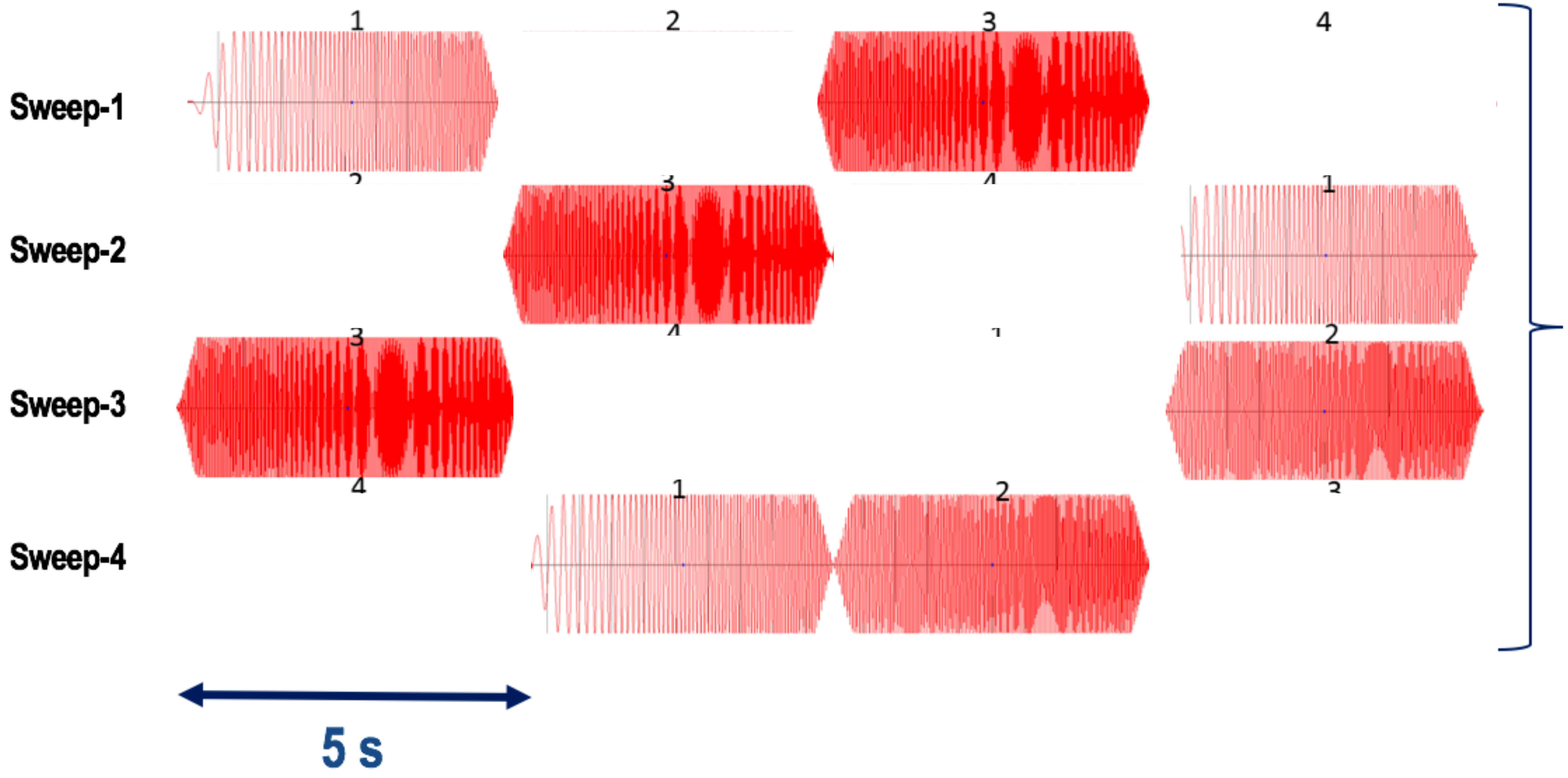
**Find representations that reveal structure = separate signal from "noise"**

- transform-domain sparsity (e.g., Fourier, curvelets, etc.)
- low-rank revealing matrix or tensor representations

**Recover by structure promotion = obtain artifact-free densely sampled data**

- sparsity via one-norm minimization, or
- nuclear-norm minimization

# Random Phase- and Frequency- encoding

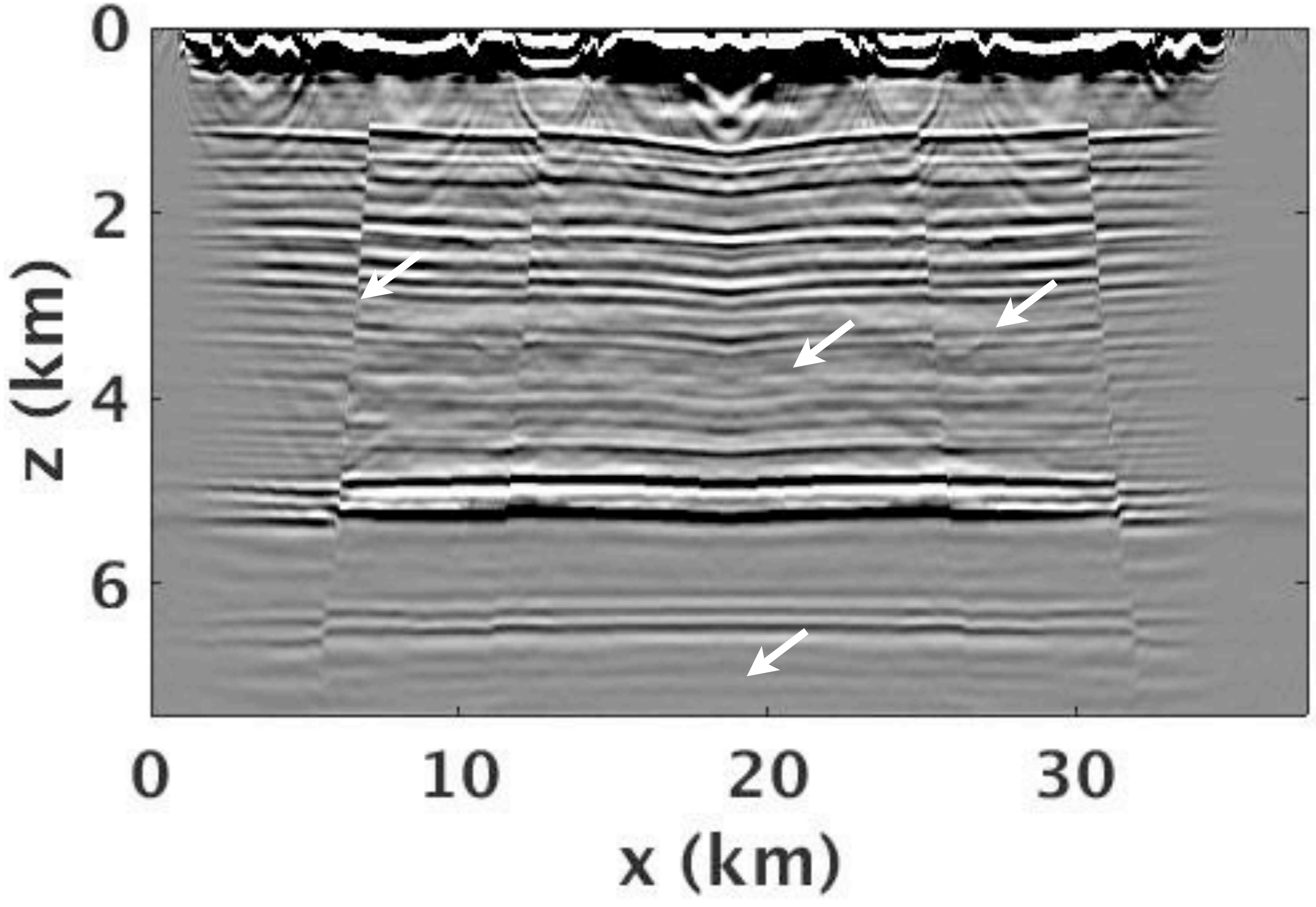



50 % subsampling

5 s each + 6s listening
22s non-concatenated
104s conventional

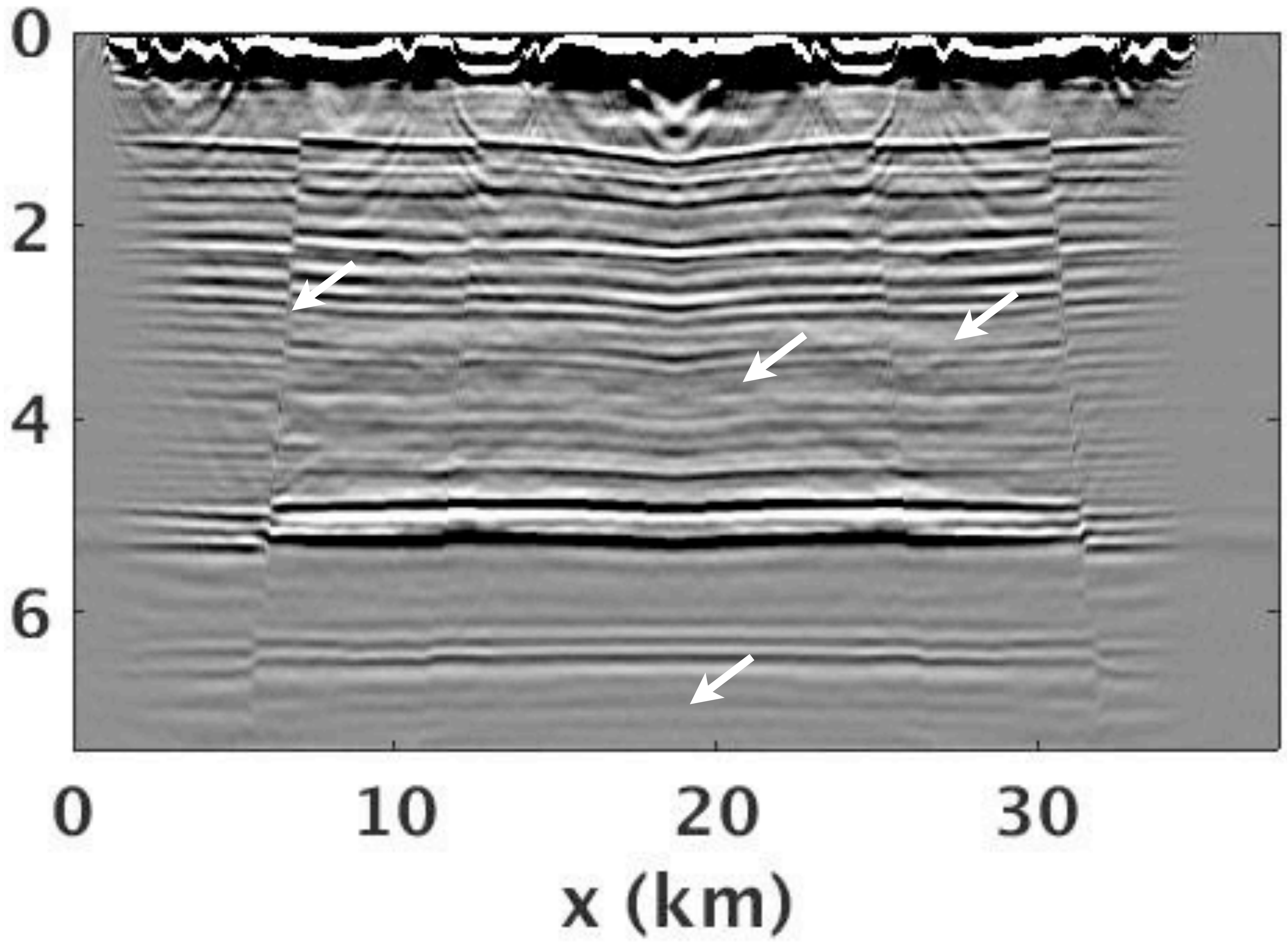
# Reverse time migration

True




After deblending & Spectral Interpolation

4-5x *speedup* in acquisition



[Candes and Plan 2010, Oropeza and Sacchi 2011]

# Matrix completion

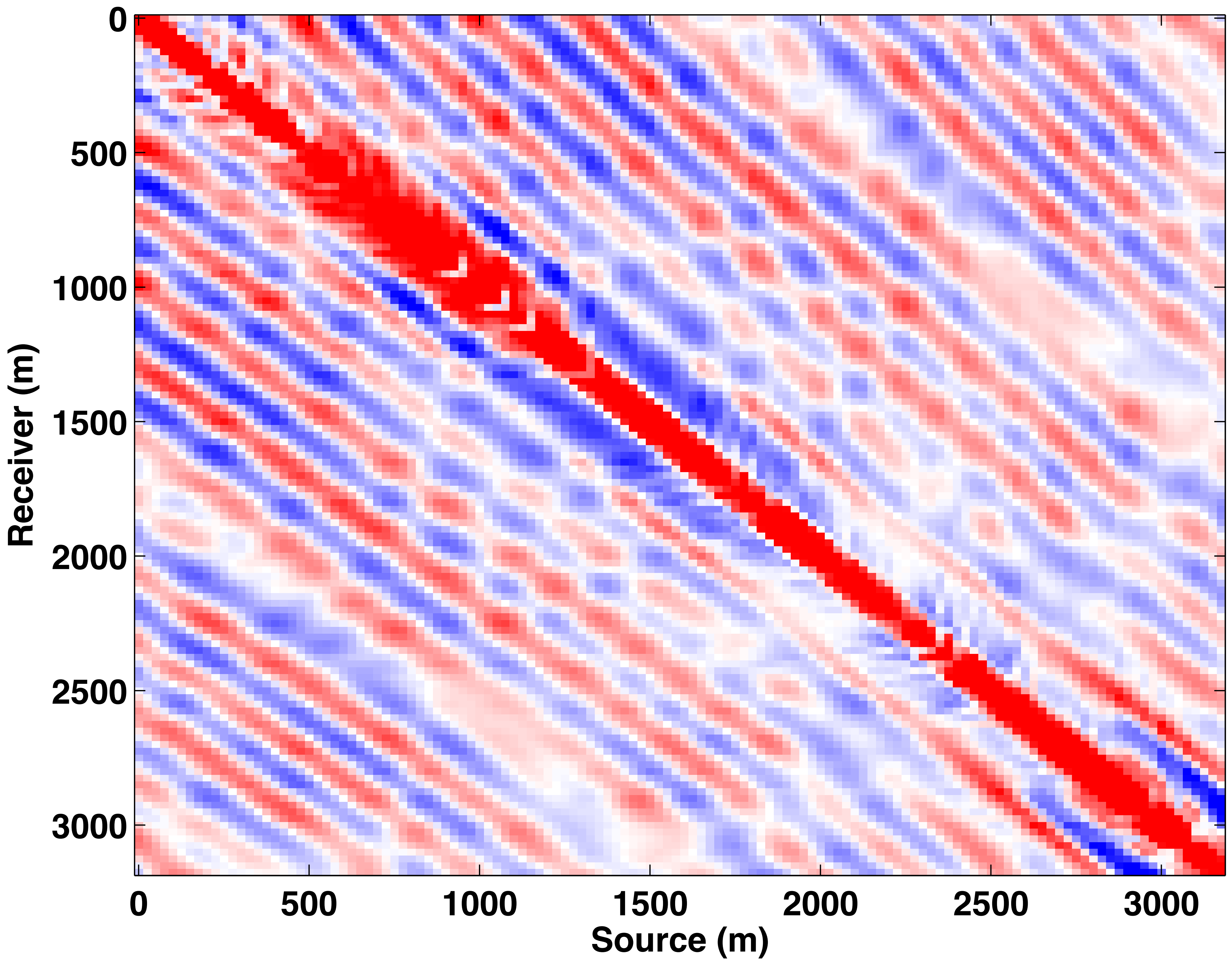
- signal structure
  - *low rank/fast decay* of singular values

- sampling scheme
  - missing data *increase* rank in "transform domain"

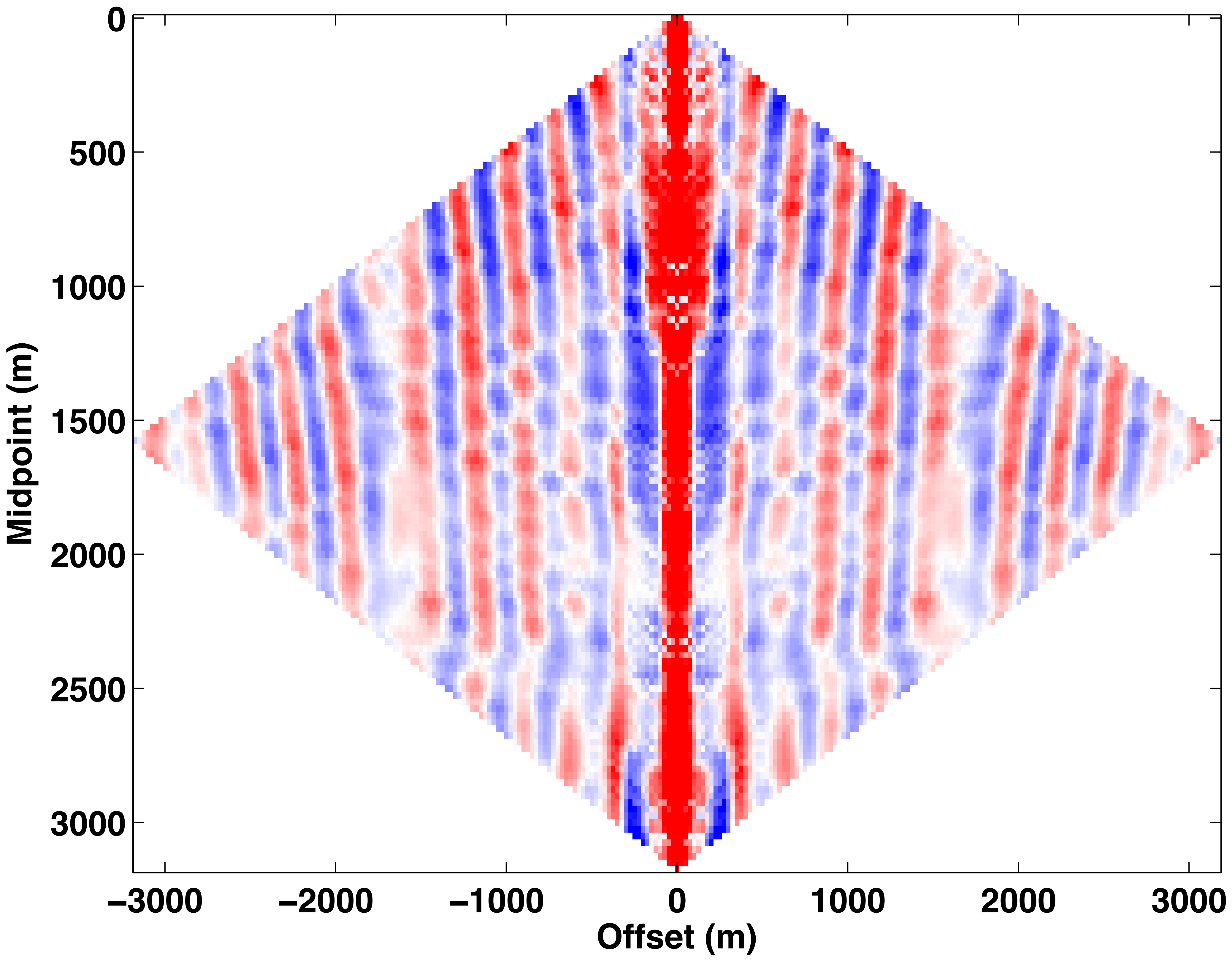
- recovery using *rank penalization* scheme

# Low-rank structure
## conventional 5D data, monochromatic slice

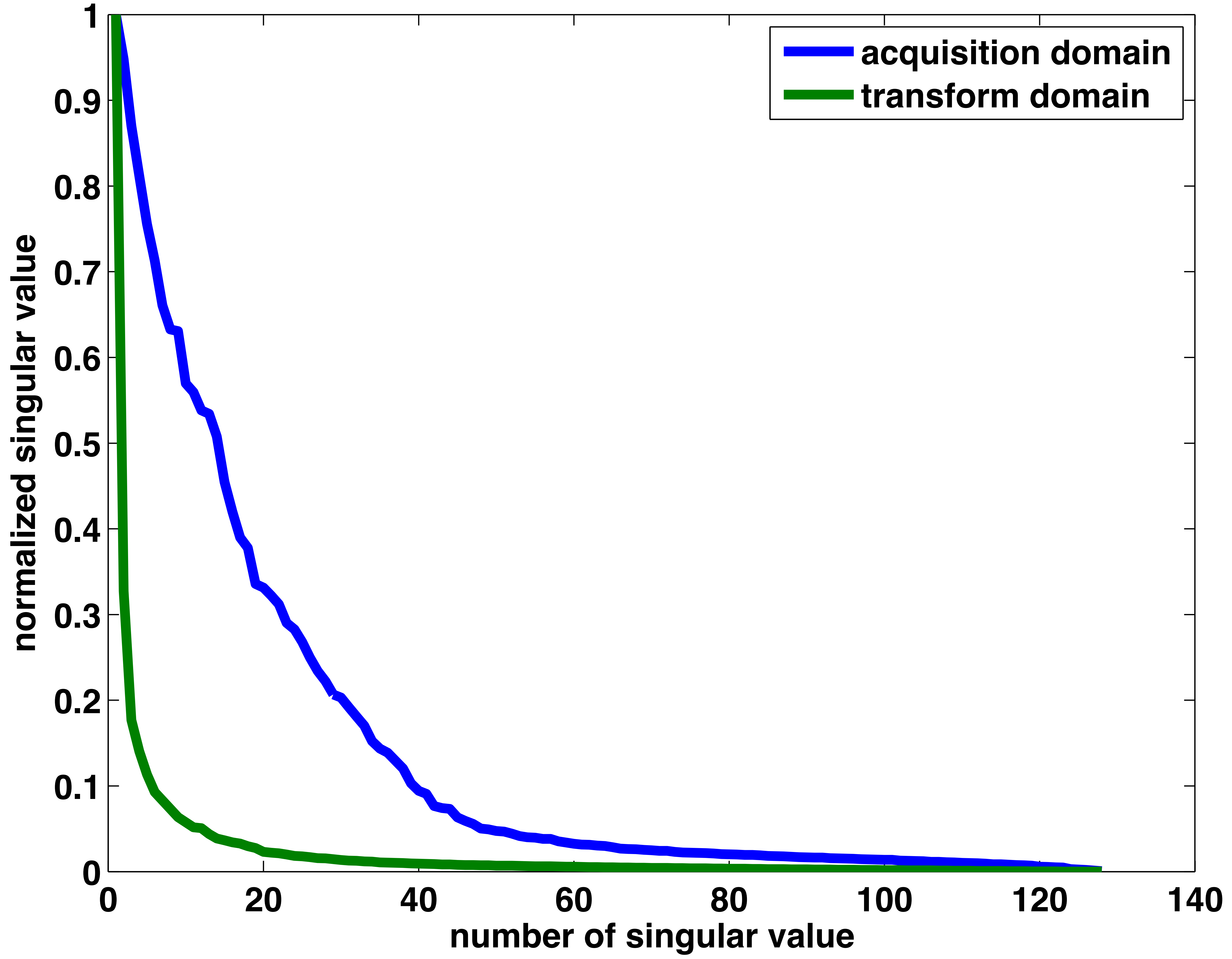
### source-receiver domain




### midpoint-offset domain



# Low-rank structure
## conventional 3D data, monochromatic slice, SVD decay

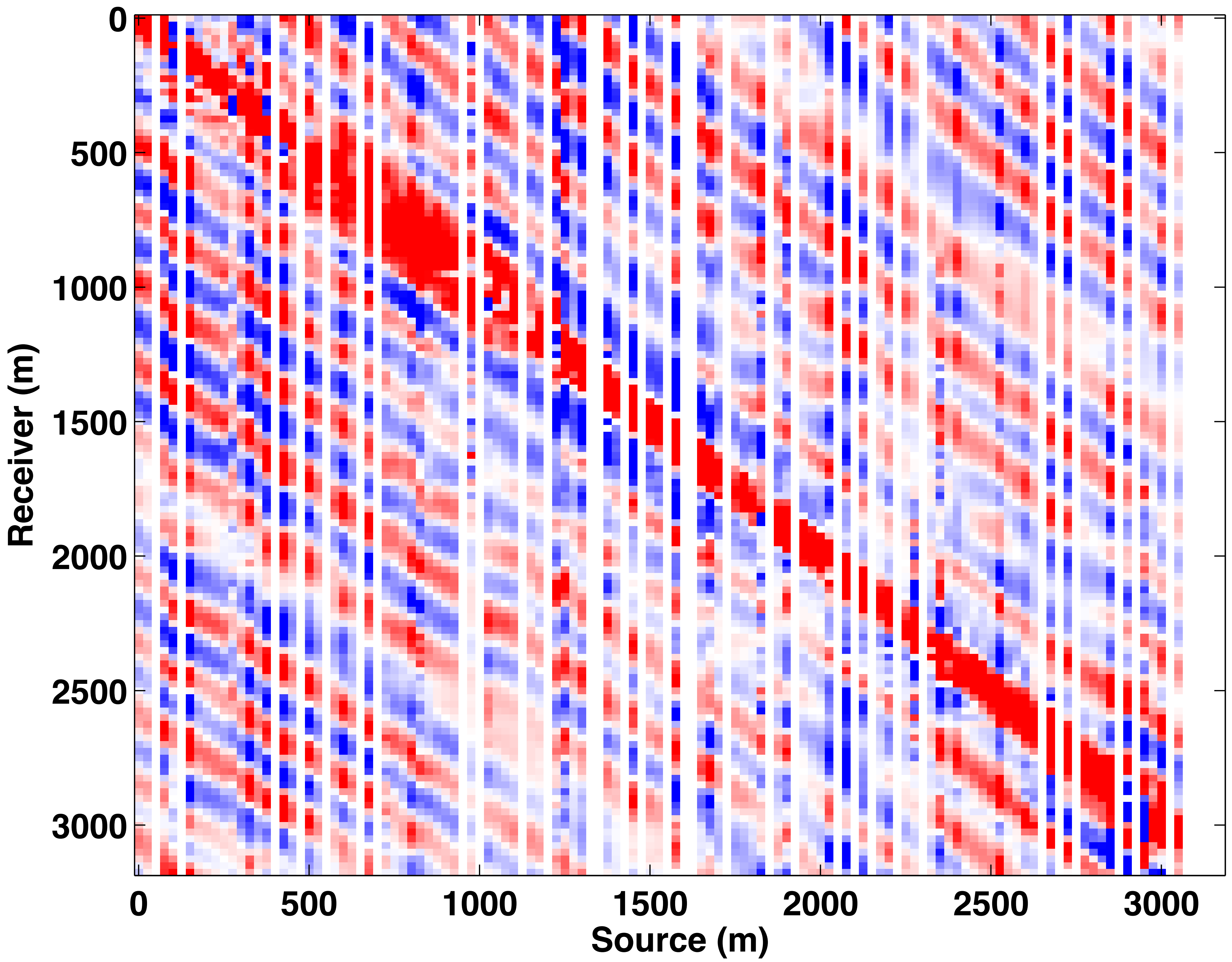


# Matrix completion

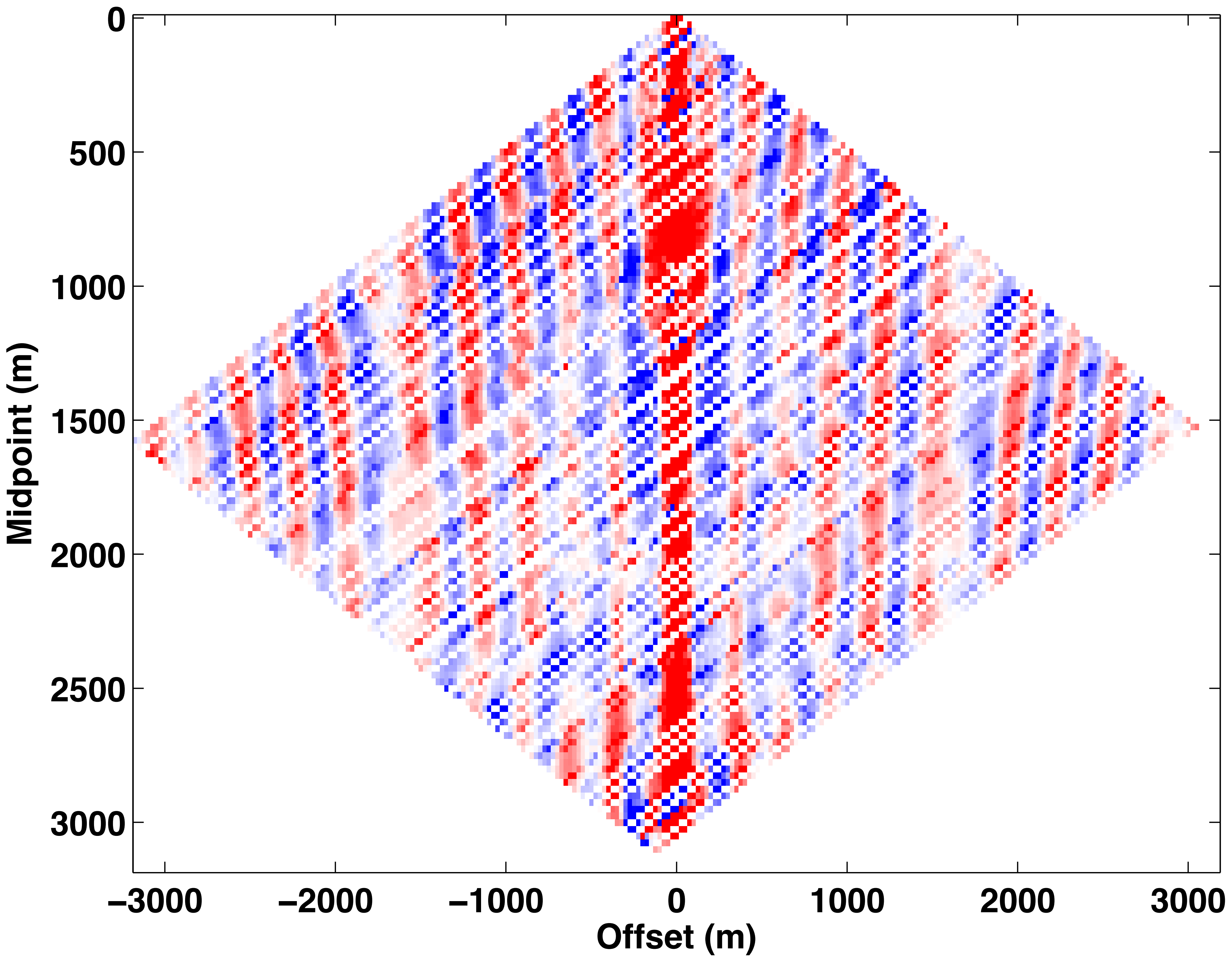
- signal structure
  - *low rank/fast decay* of singular values
- sampling scheme
  - missing data *increase* rank in "transform domain"
- recovery using *rank penalization* scheme

# Low-rank structure
## pseudo-deblended data, monochromatic slice

### source-receiver domain

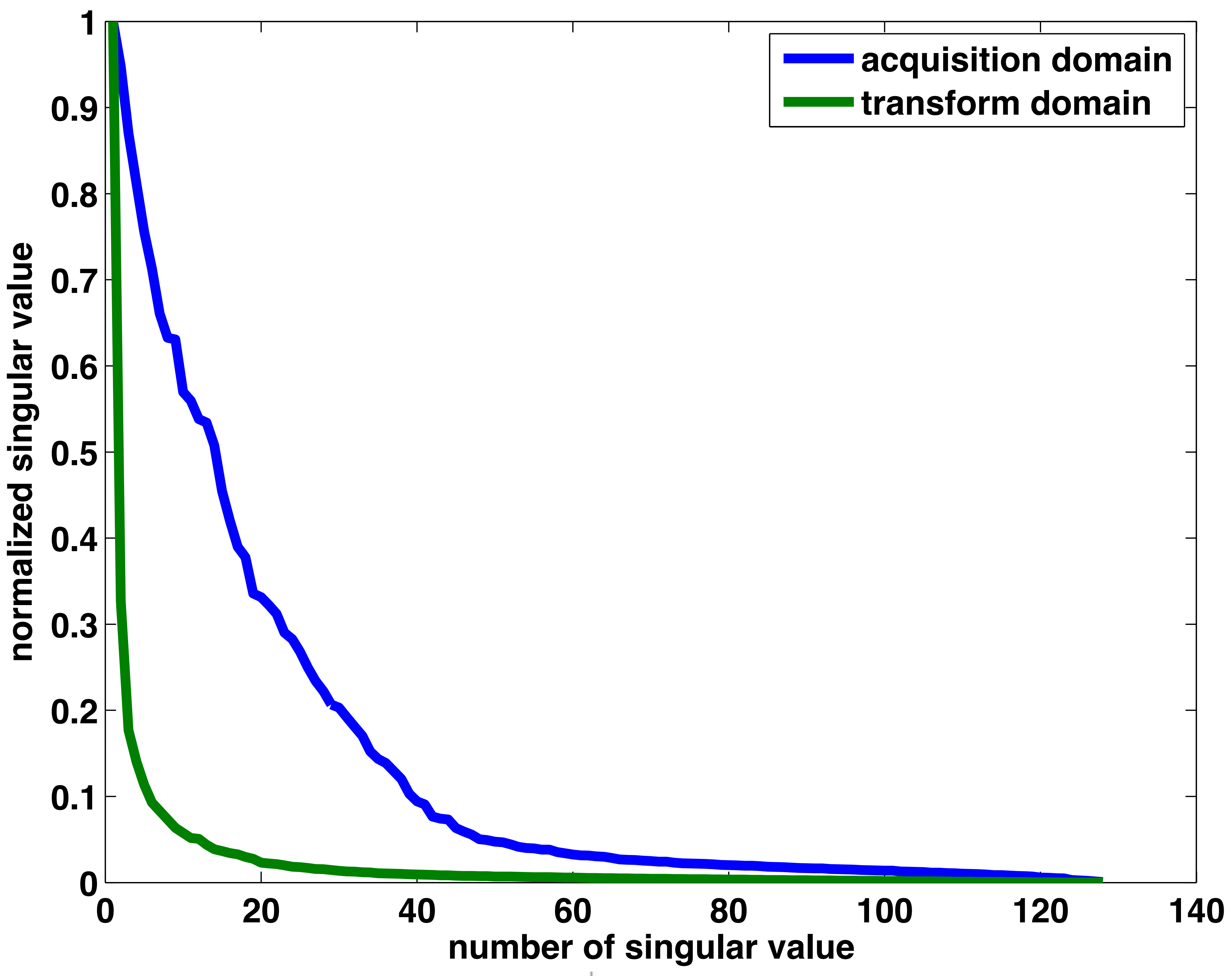



### midpoint-offset domain

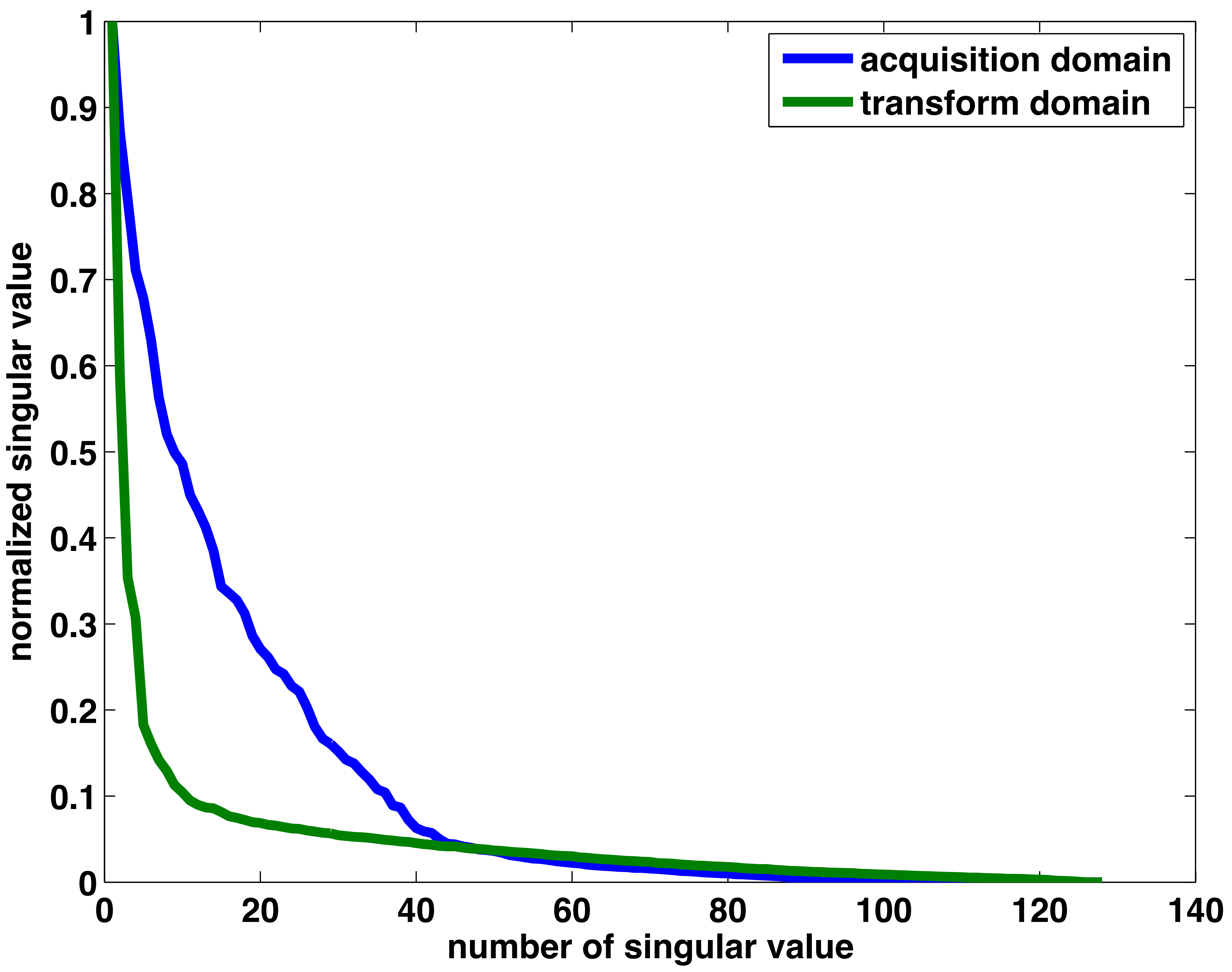


# Low-rank structure
## pseudo-deblended data, monochromatic slice

**Fully sampled**




**After deblending**



# Matrix completion

- signal structure
  - *low rank/fast decay* of singular values
- sampling scheme
  - missing data *increase* rank in "transform domain"
- recovery using *rank penalization* scheme

# Nuclear-norm minimization

[Recht et. al., 2010]

$$\min_{\mathbf{X}} \quad \underbrace{||\mathbf{X}||_*}_{\text{sum of singular values of } \mathbf{X}} \quad \text{s.t.} \quad \|\mathcal{A}(\mathbf{X}) - \mathbf{b}\|_2 \leq \epsilon$$

where

$$\mathcal{A} = \mathbf{F}_t^{-1}\mathbf{R}\mathbf{B}\mathcal{S}^H$$

| | |
|---|---|
| $\mathbf{F}$ | Temporal-Fourier transform |
| $\mathbf{R}$ | Restriction operator |
| $\mathcal{S}$ | Midpoint-offset operator |
| $\mathbf{B}$ | Blending and convolution operator |

# Nuclear-norm minimization

[Recht et. al., 2010]

$$\mathbf{B} = \begin{bmatrix} \mathbf{B}_1 & & \\ & \ddots & \\ & & \mathbf{B}_k \end{bmatrix}$$

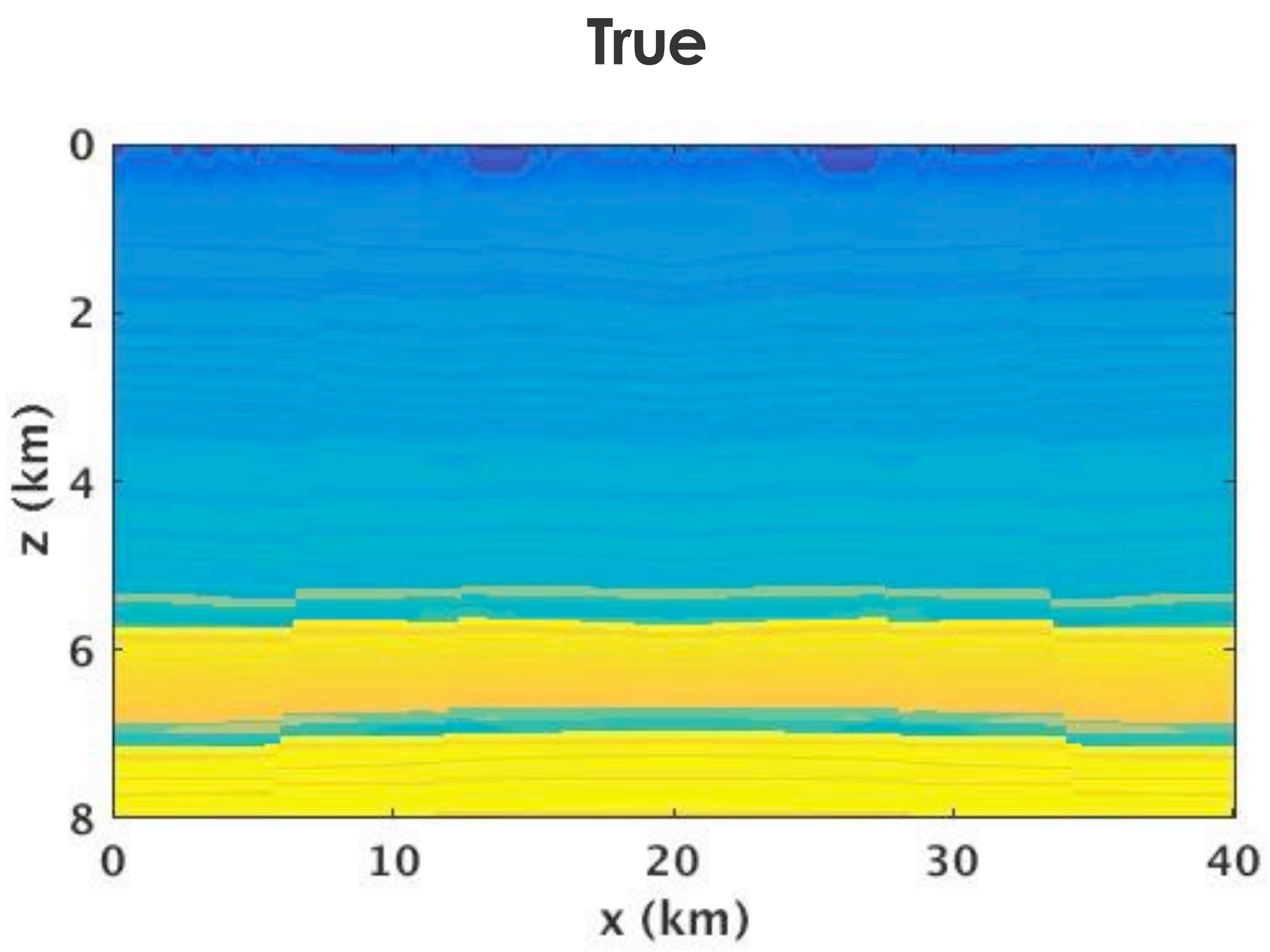
where

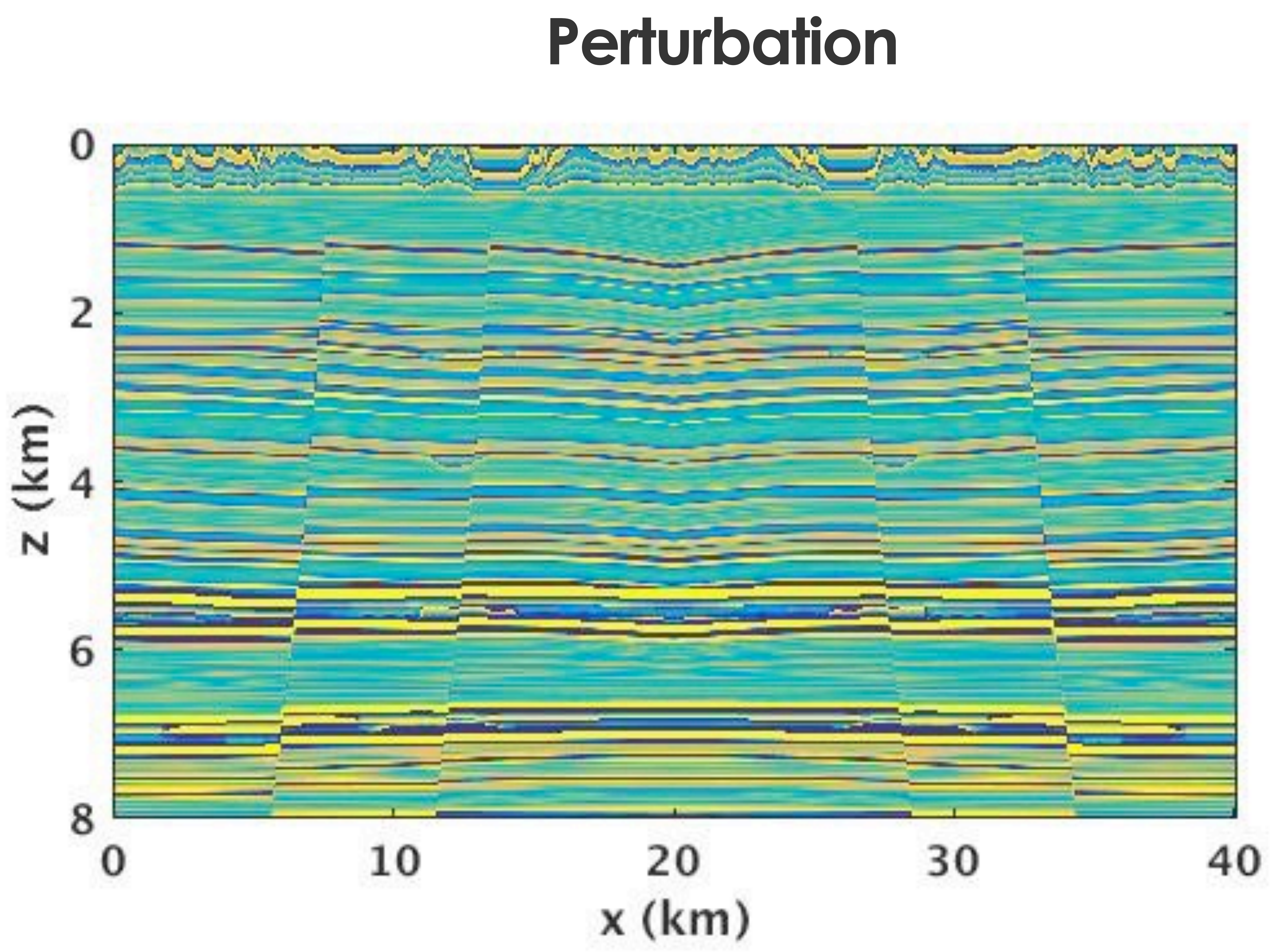
$$\mathbf{B}_i = \begin{pmatrix} \mathrm{diag}(a_1) & \mathrm{diag}(a_2) & \mathrm{diag}(a_3) & \mathrm{diag}(a_4) \\ \mathrm{diag}(a_2) & \mathrm{diag}(a_3) & \mathrm{diag}(a_4) & \mathrm{diag}(a_1) \\ \mathrm{diag}(a_3) & \mathrm{diag}(a_4) & \mathrm{diag}(a_1) & \mathrm{diag}(a_2) \\ \mathrm{diag}(a_4) & \mathrm{diag}(a_1) & \mathrm{diag}(a_2) & \mathrm{diag}(a_3) \end{pmatrix}$$

$a_1, a_2, a_3, a_4$ Four sweep segments and $k = \dfrac{N_s}{n}$

# 2D SEAM Model

# SEAM Land Model



# Acquisition parameters


720 sources and receivers sampled at 50 m

Four vibrators separated by 250 m

Green's function is simulated using ricker wavelet with central frequency of 25 Hz

Convolved w/ sweep to generate synthetic data

# Acquisition parameters

**Underlying grid:**

720 sources and receivers sampled at 50 m

Four vibrators separated by 250 m

Ricker wavelet with central frequency of 25 Hz

**4 – 5 X cost reduction**

- thanks to CS based acquisition design

# Optimization information

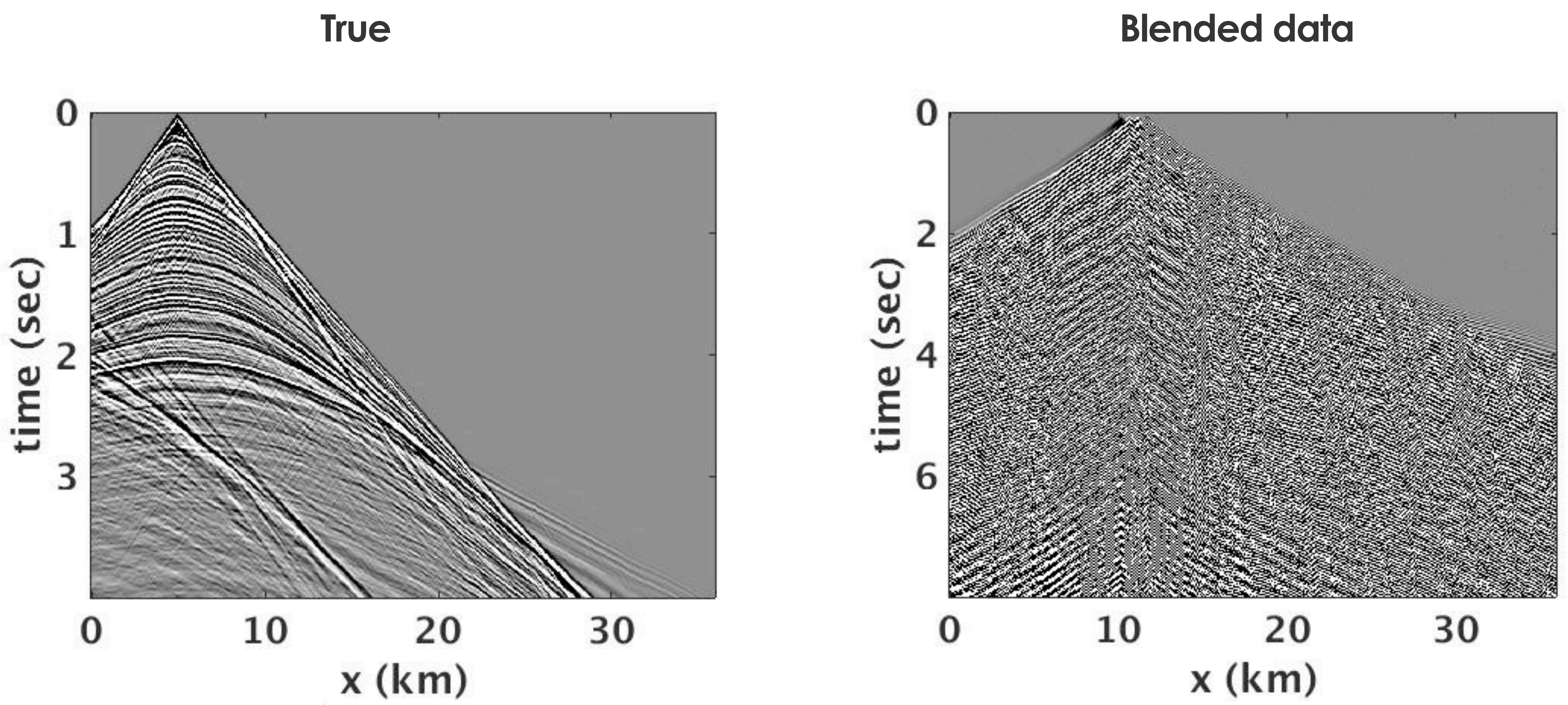
Parallelized factorization framework over sources & receivers

Number of iterations: 200

Computational time / frequency slice: 1 hour 10 minutes

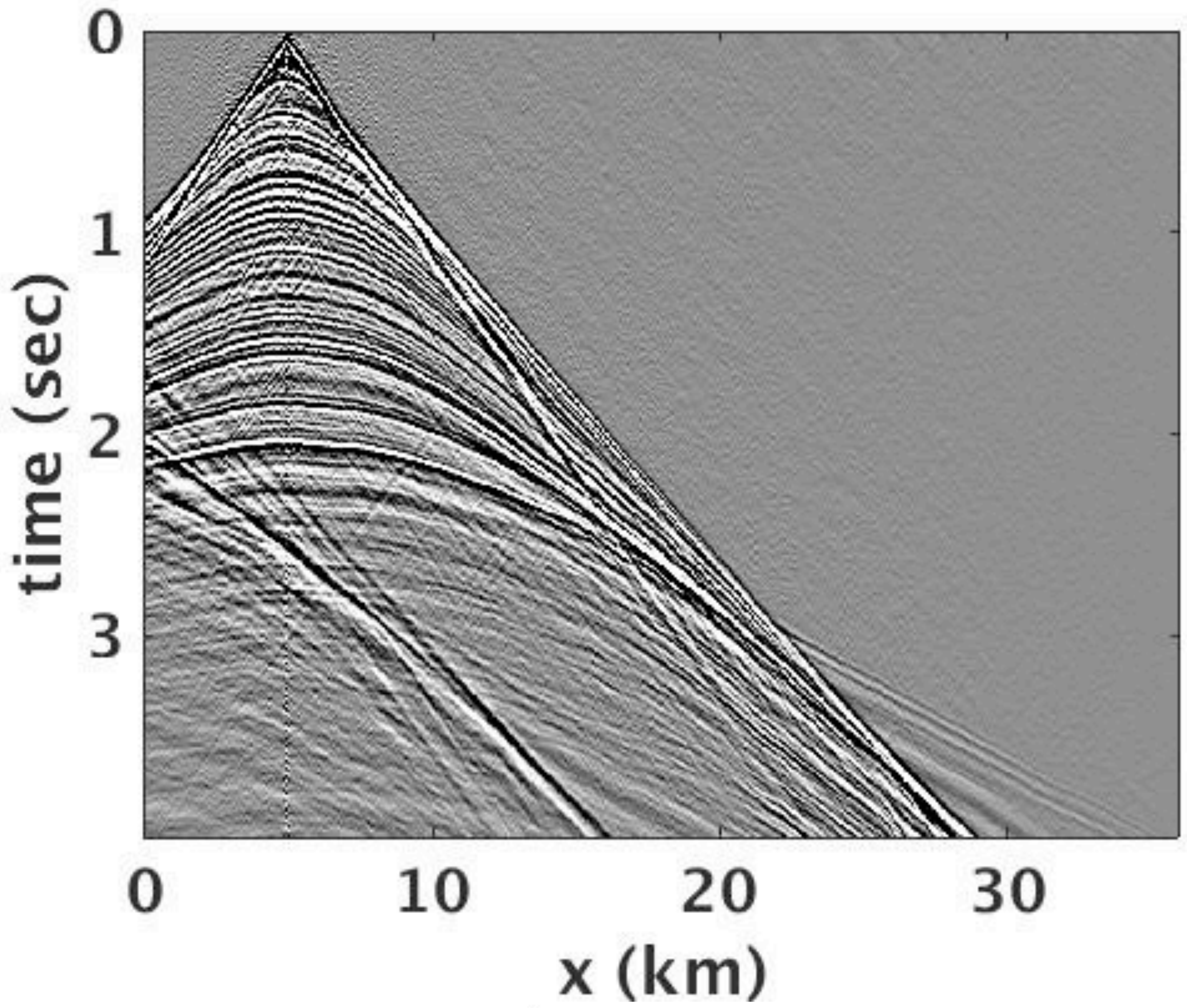
Computational resource / frequency slice: 1 node w/ 128 GB RAM, 20-core processors, and multithreading

# Deblending and Spectral Interpolation

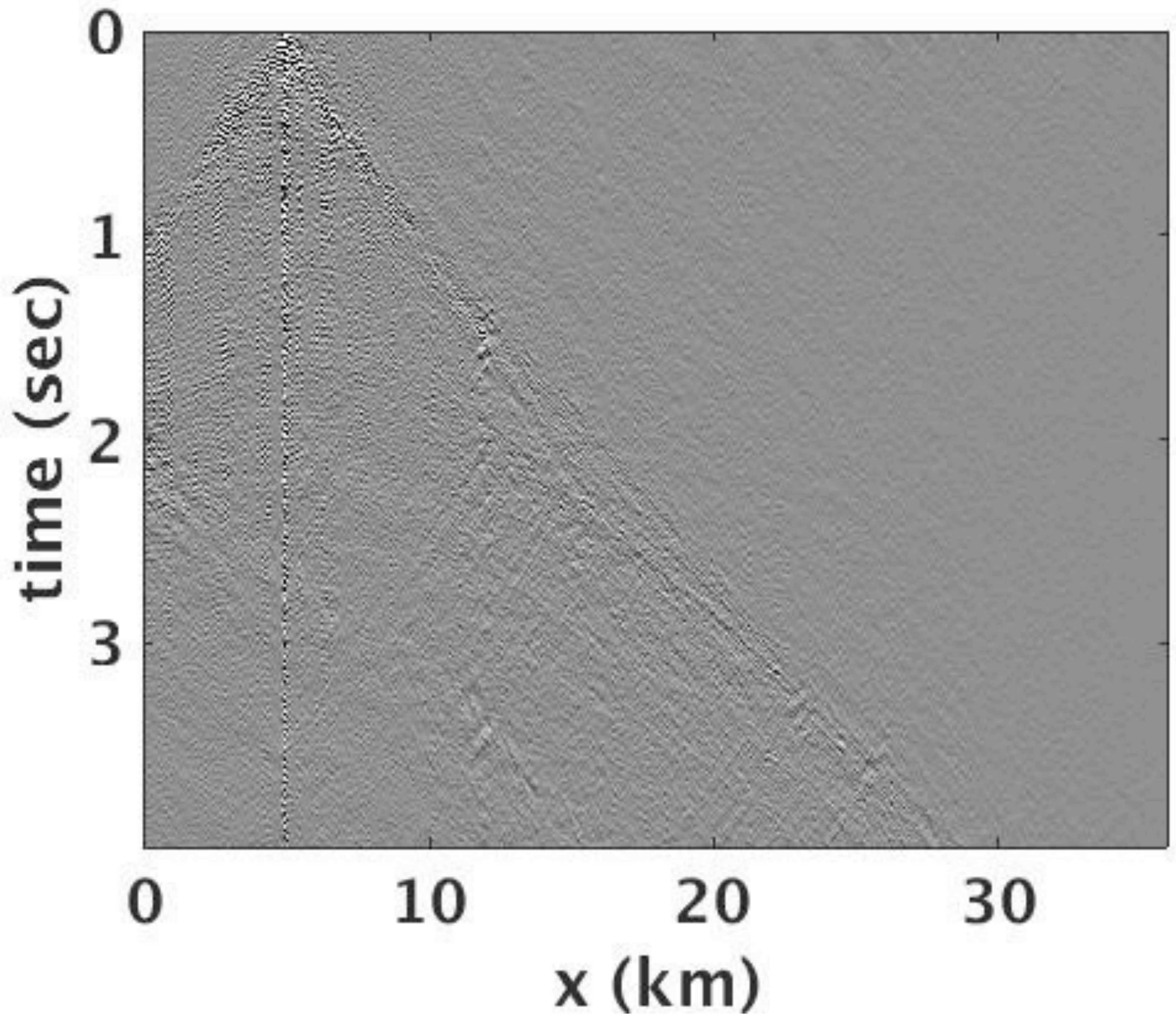


# Deblending and Interpolation

Recovery
SNR = 21 dB

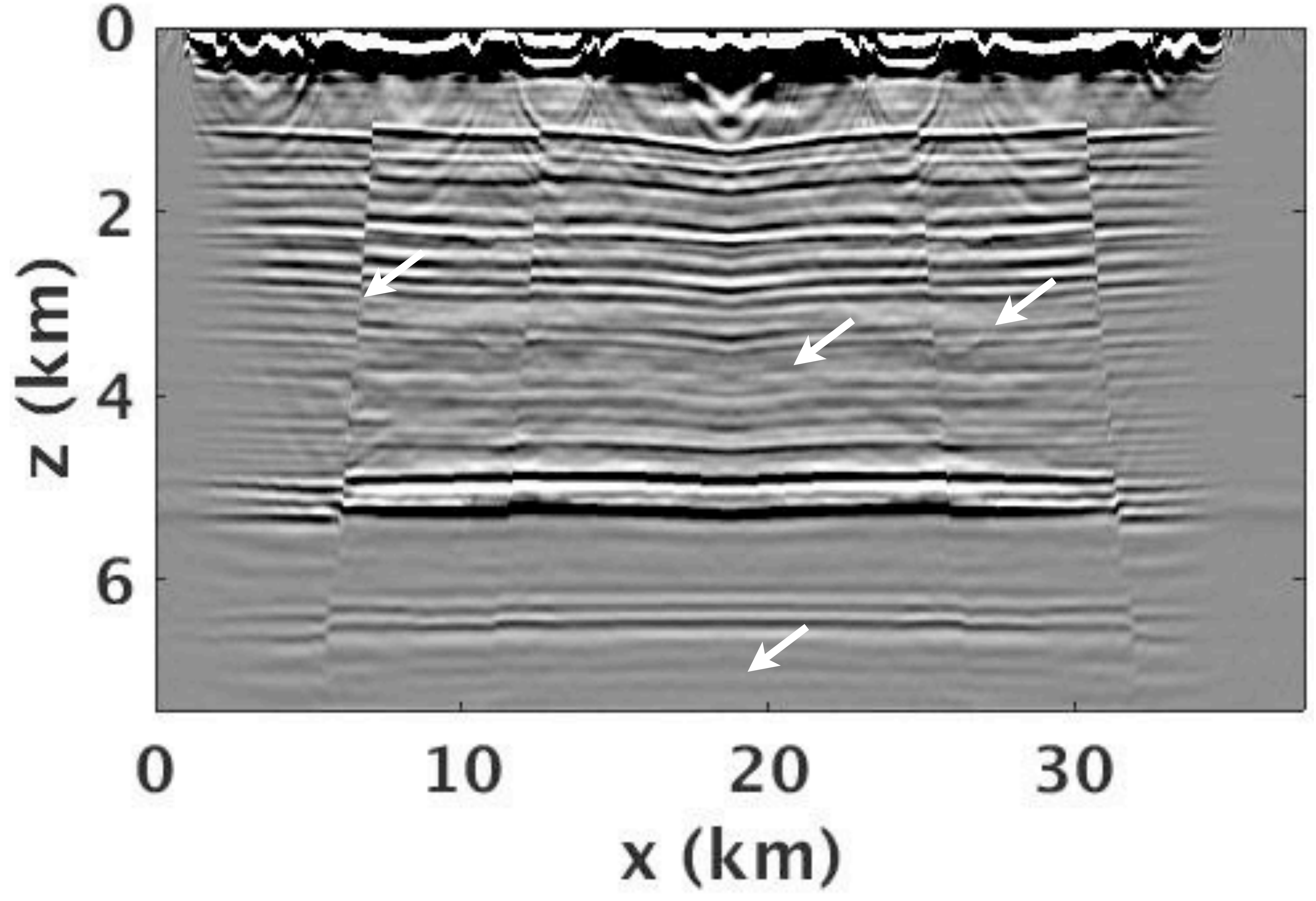



Residual

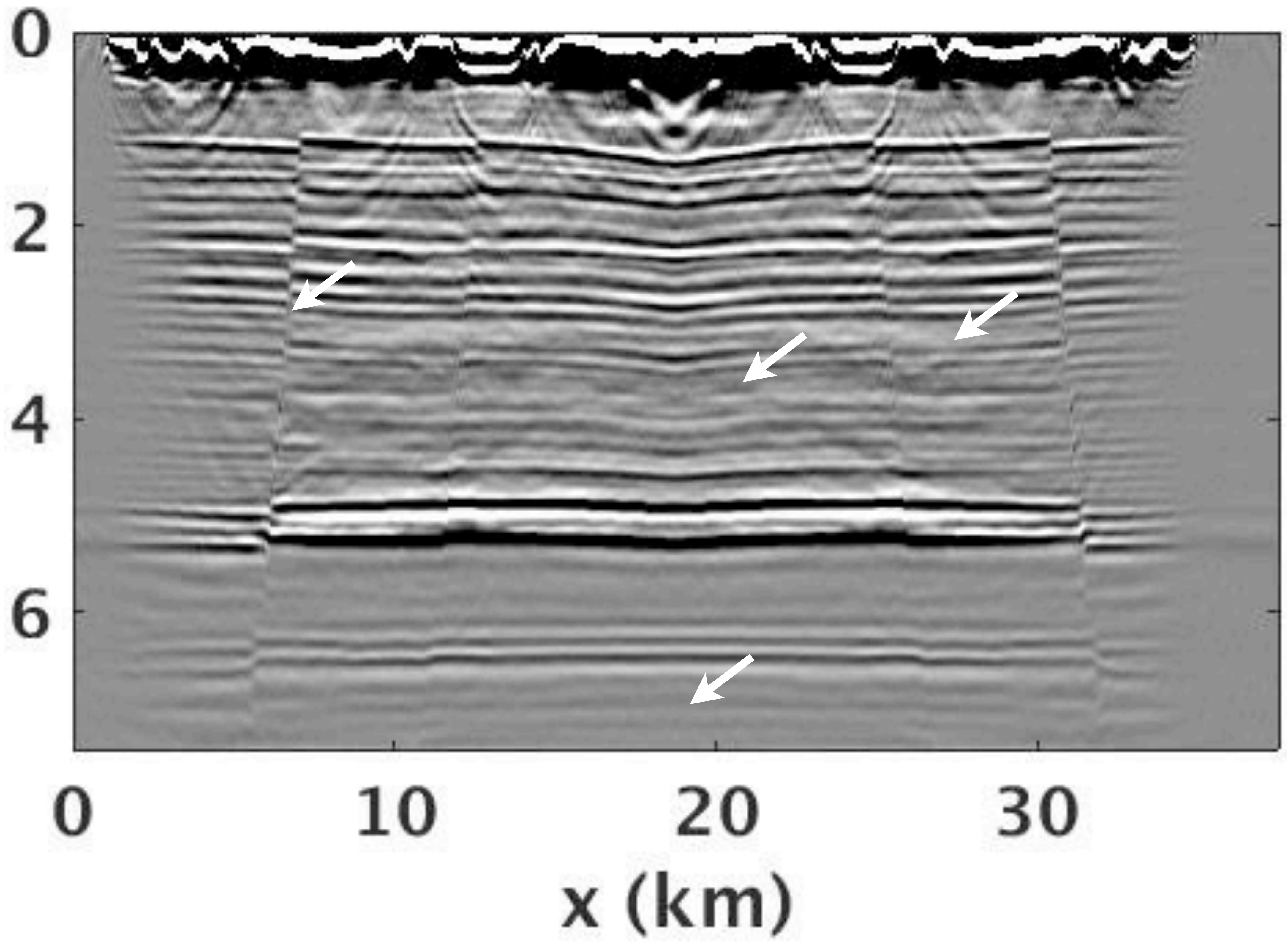


# Reverse time migration

True

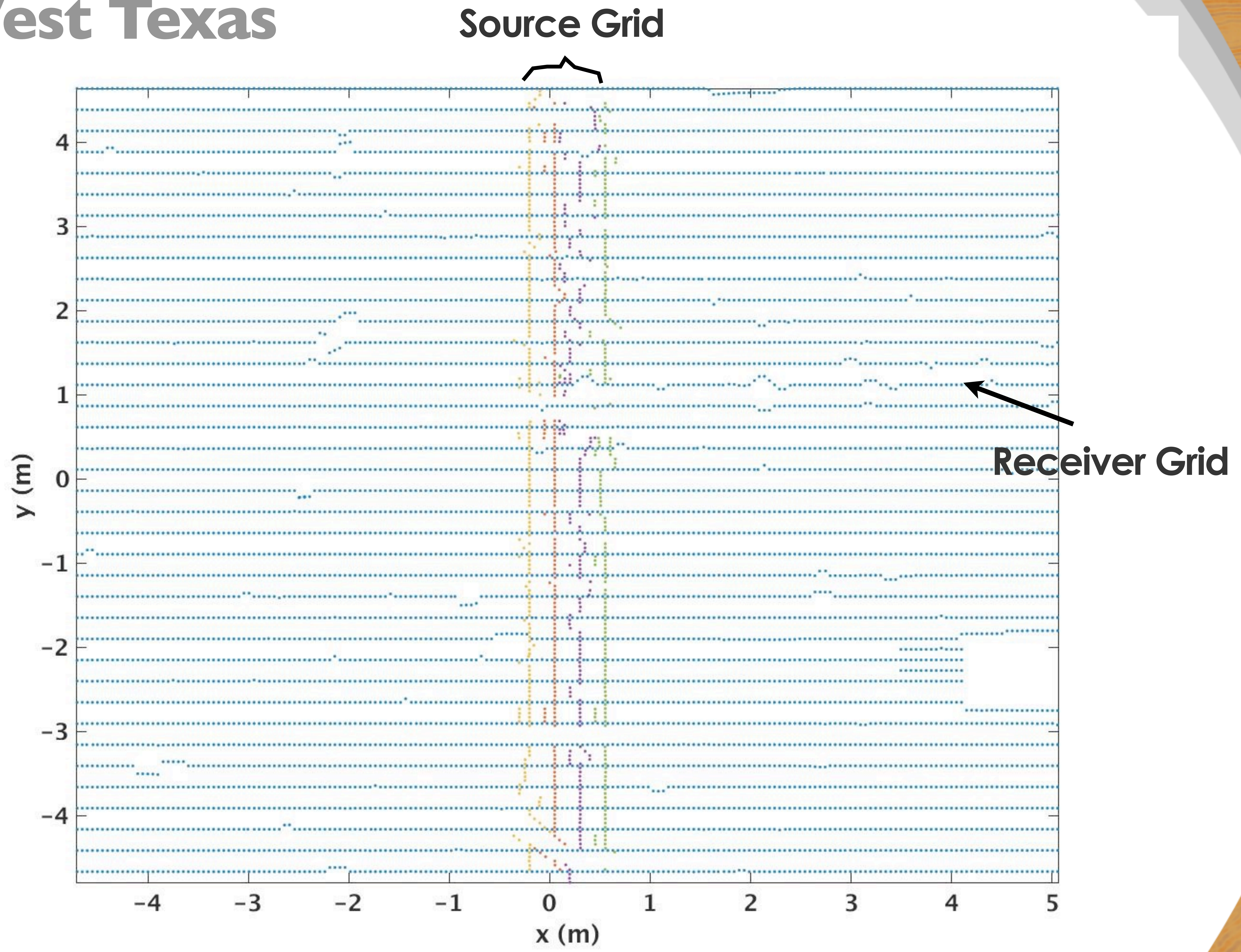



After deblending & Spectral Interpolation



# 3D Acquisition — West Texas

# Real data—West Texas



# Acquisition Parameters

Source line interval = Receiver line interval = 825 ft

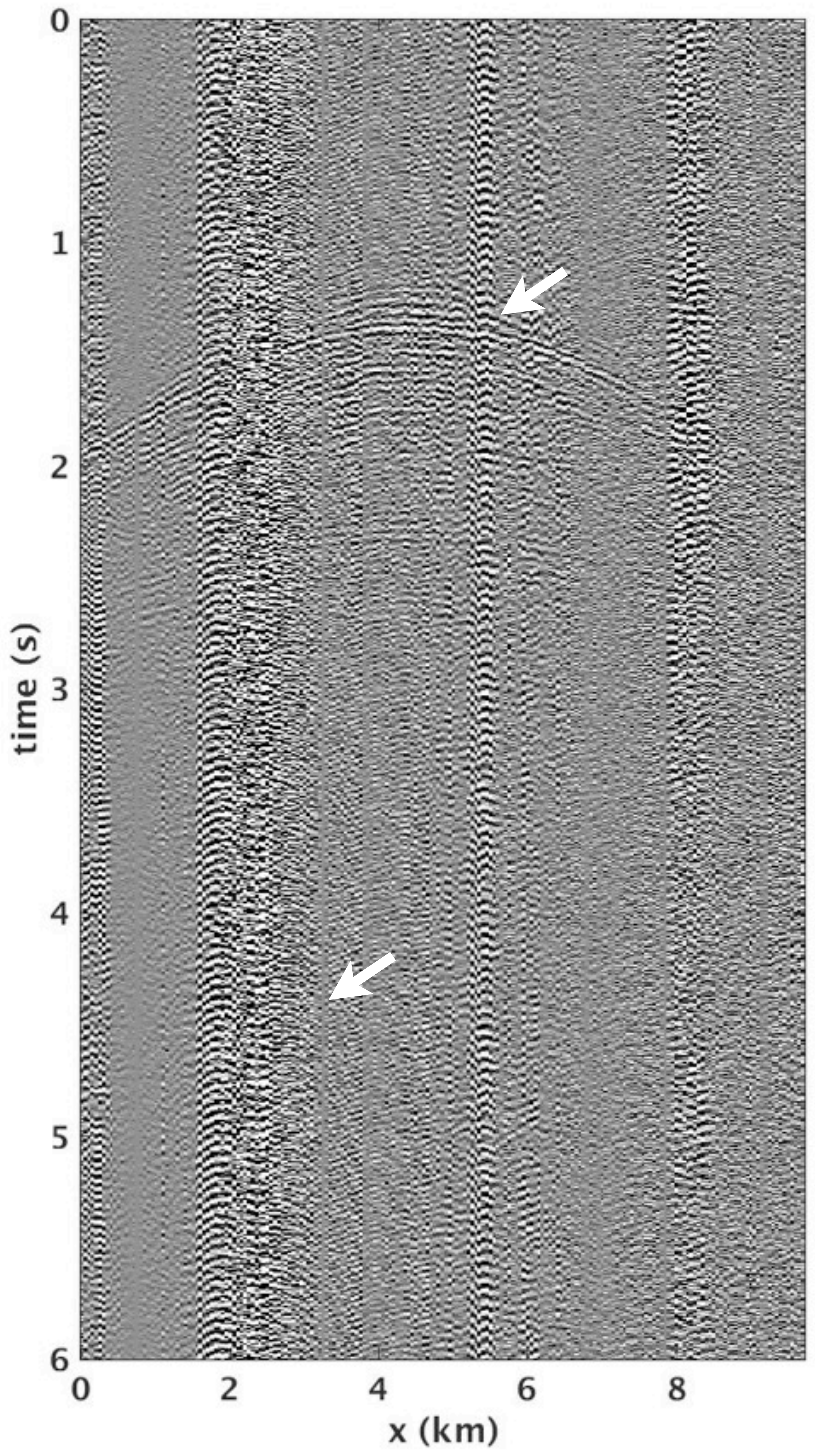
Source point interval=receiver point interval=165 ft

756 shots,  7400 receiver for each shot

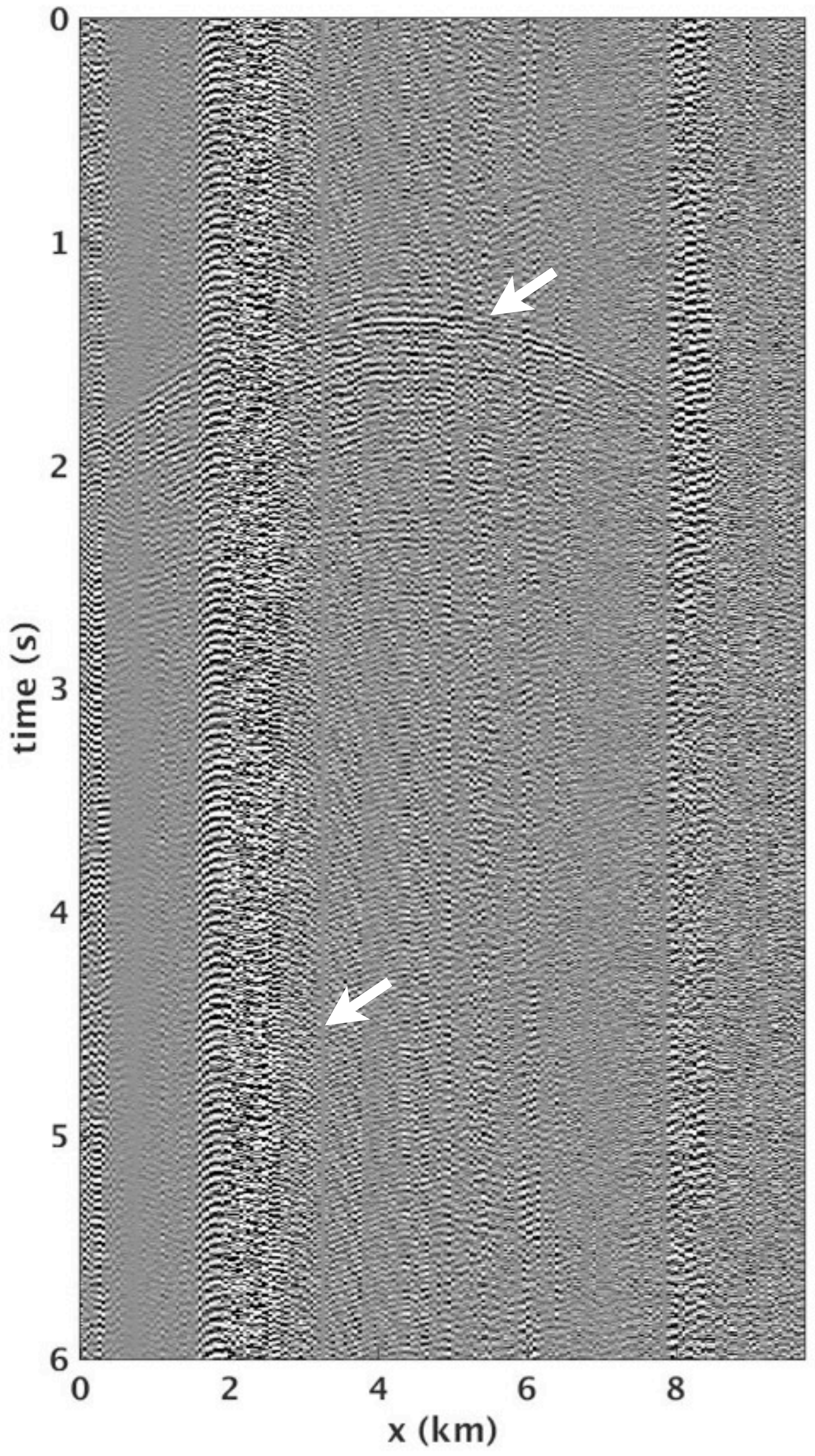
4 different sweeps combination

# Adjoint
# w/ & w/o sweeps subsampling

w/




w/o




***Benefits***

**4-5x *speedup* in acquisition**

**record *less* noise**

Robust principal component analysis, Candes et. al., 2011, Journal of the ACM

Coherent and random noise attenuation using the curvelet transform, Neelamani et. al., The Leading Edge, 2008

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# Deblending and Spectral Interpolation process

Apply adjoint

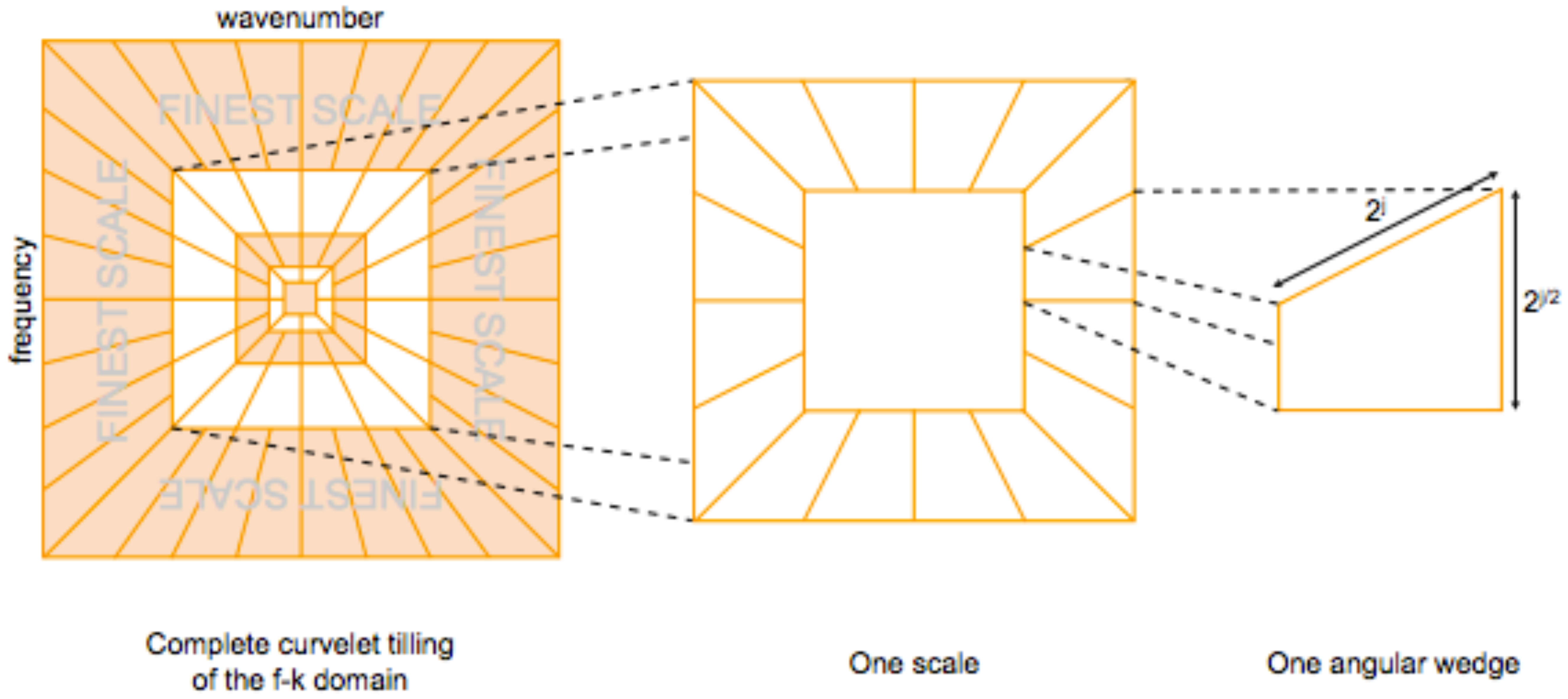
Remove ground roll

Blend ground roll and subtract from field data

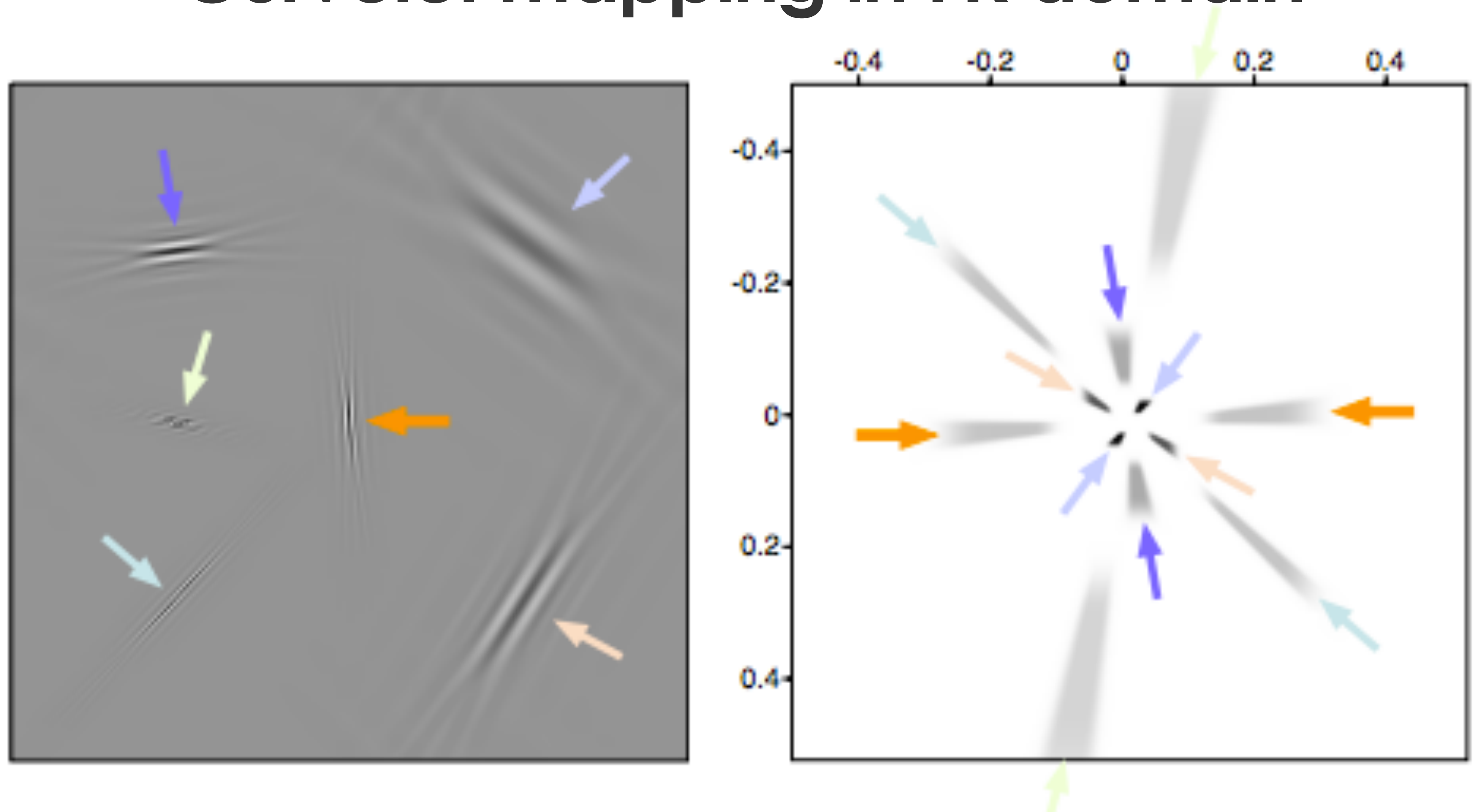
Run deblending & spectral interpolation

# Ground roll removal

# Curvelet transform




## Curvelet mapping in FK domain



Rajiv Kumar, Nick Moldoveanu, and Felix J. Herrmann, "Denoising high-amplitude cross-flow noise using curvelet-based stable principle component pursuit", 2017

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# Noise mapping in curvelet domain

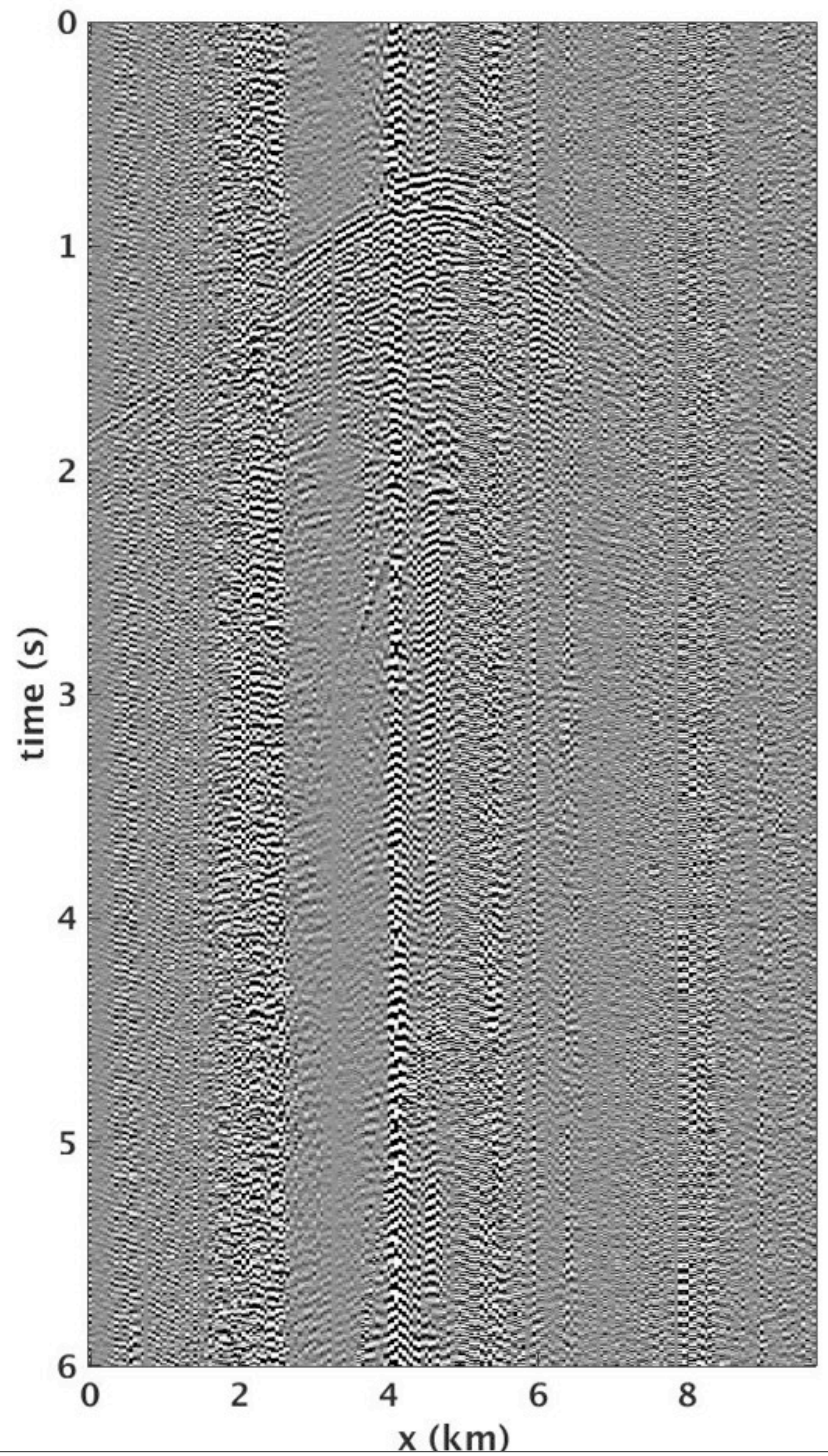
Different morphological appearances of noise & signal in curvelet domain

Noise & signal map to different angular wedges w/ distinct dip characteristics

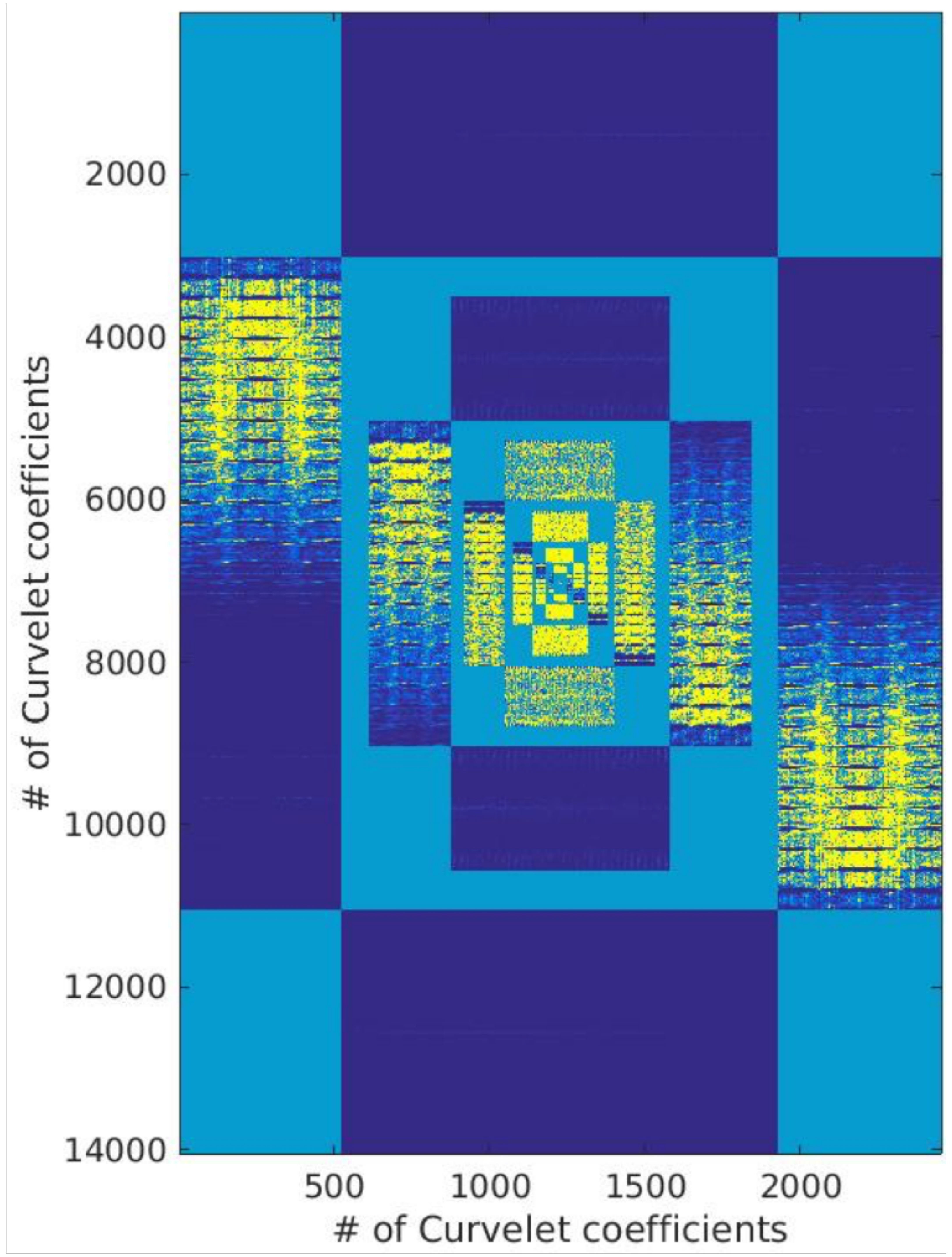
Coherent noise is generally low-rank

Seismic reflection & diving waves are sparse

# Curvelet representation

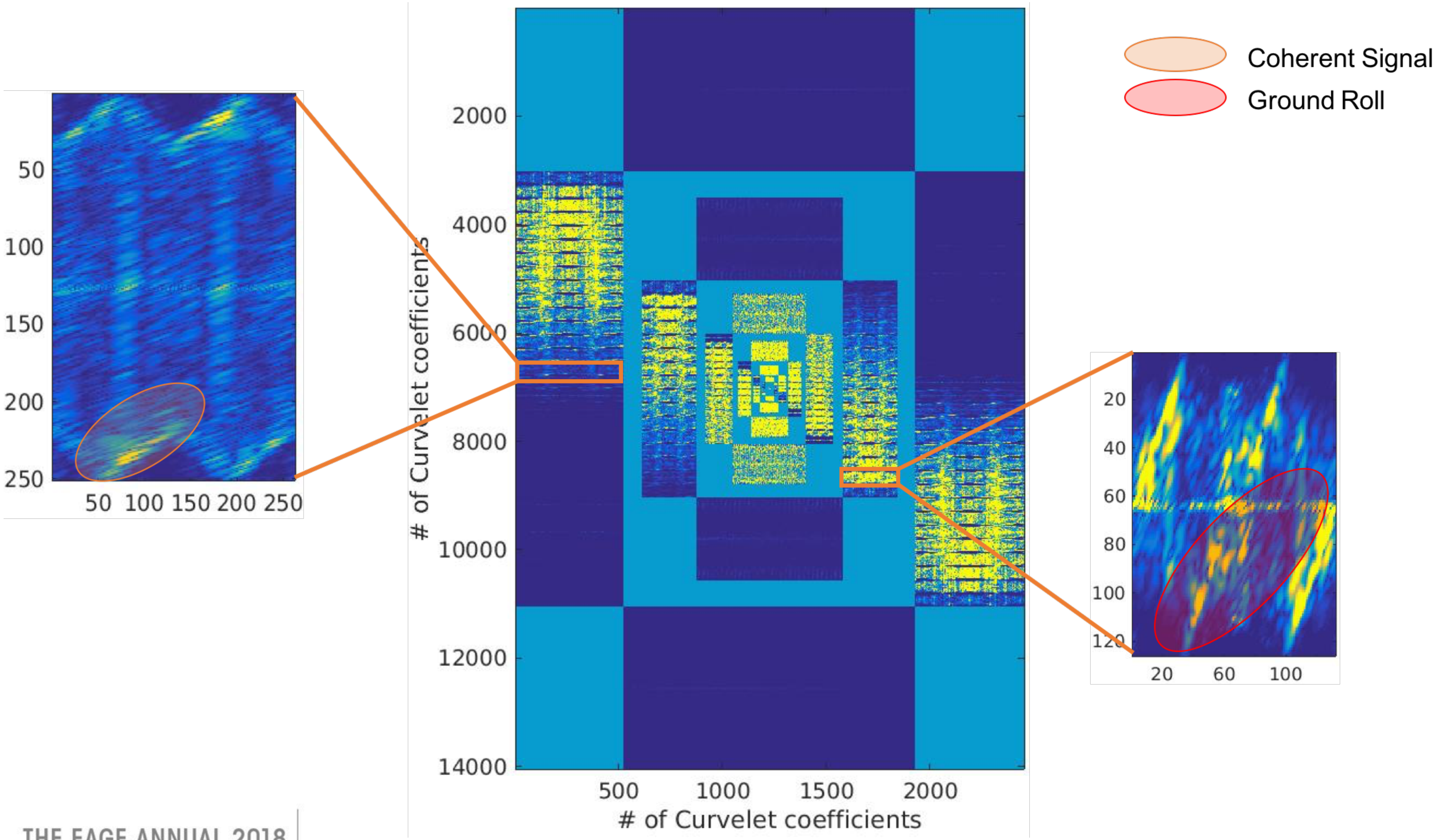



**Forward Curvelet transform**



# Ground roll in curvelet domain





Robust principal component analysis, Candes et. al., 2011, Journal of the ACM

Coherent and random noise attenuation using the curvelet transform, Neelamani et. al., The Leading Edge, 2008

Denoising high-amplitude cross-flow noise using curvelet-based stable principle component pursuit, Kumar et. al., 2017



# Principal component pursuit

Let $\mathbf{Y} = \mathbf{L} + \mathbf{S}$ , where $\mathbf{Y}$ is observed data, $\mathbf{L}$ is low-rank noise component and $\mathbf{S}$ is sparse seismic reflection and diffraction events.
Principle component pursuit solves:

$$\min_{(\mathbf{L},\mathbf{S})} \quad \|\mathbf{L}\|_* + \lambda\|\mathbf{S}\|_1 \quad \text{subject to} \quad \mathbf{L} + \mathbf{S} = \mathbf{Y},$$

where

$$\|\mathbf{L}\|_* = \sum_i \sigma_i(\mathbf{L}) \quad \text{and} \quad \|\mathbf{S}\|_1 = \sum_{i,j} |\mathbf{S}_{i,j}|$$

Robust principal component analysis, Candes et. al., 2011, Journal of the ACM

Coherent and random noise attenuation using the curvelet transform, Neelamani et. al., The Leading Edge, 2008

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# Principal component pursuit

Solve the following augmented Lagrangian system:

$$l(\mathbf{L}, \mathbf{S}, \mathbf{P}) = \min_{(\mathbf{L},\mathbf{S},\mathbf{P})} \quad \|\mathbf{L}\|_* + \lambda\|\mathbf{S}\|_1 \quad + \langle \mathbf{P}, \mathbf{Y} - \mathbf{L} - \mathbf{S} \rangle \quad + \frac{\mu}{2}\|\mathbf{Y} - \mathbf{L} - \mathbf{S}\|_F^2$$

Use alternating direction method

Each variable is solved using gradient decent followed by soft-thresholding

Robust principal component analysis, Candes et. al., 2011, Journal of the ACM

Coherent and random noise attenuation using the curvelet transform, Neelamani et. al., The Leading Edge, 2008

# Principal component pursuit

Initialize $\mathbf{S}_0 = \mathbf{P}_0 = \mathbf{0}, \mu > \mathbf{0}, \lambda > \mathbf{0}$

for $k = 0, ..., n$

$$\mathbf{L}_{k+1} = \mathcal{D}_{\mu^{-1}}(\mathbf{Y} - \mathbf{S}_k + \mu^{-1}\mathbf{P}_k)$$

$$\mathbf{S}_{k+1} = \mathcal{S}_{\lambda\mu^{-1}}(\mathbf{Y} - \mathbf{L}_{k+1} + \mu^{-1}\mathbf{P}_k)$$

$$\mathbf{P}_{k+1} = \mathbf{P}_k + \mu(\mathbf{Y} - \mathbf{L}_{k+1} - \mathbf{S}_{k+1})$$

end

where

$$\mathcal{S}_\tau[x] = \text{sgn}(x) \times \max(\|x\| - \tau, 0)$$

$$\mathcal{D}_\tau[\mathbf{X}] = \mathbf{U}\mathcal{S}_\tau(\mathbf{\Sigma})\mathbf{V}^*$$

Robust principal component analysis, Candes et. al., 2011, Journal of the ACM

Coherent and random noise attenuation using the curvelet transform, Neelamani et. al., The Leading Edge, 2008

# Denoising framework

Perform 2D curvelet transform on each shot gather

Extract noisy curvelet coefficients along parabolic angular wedges at each scale and organize into a matrix

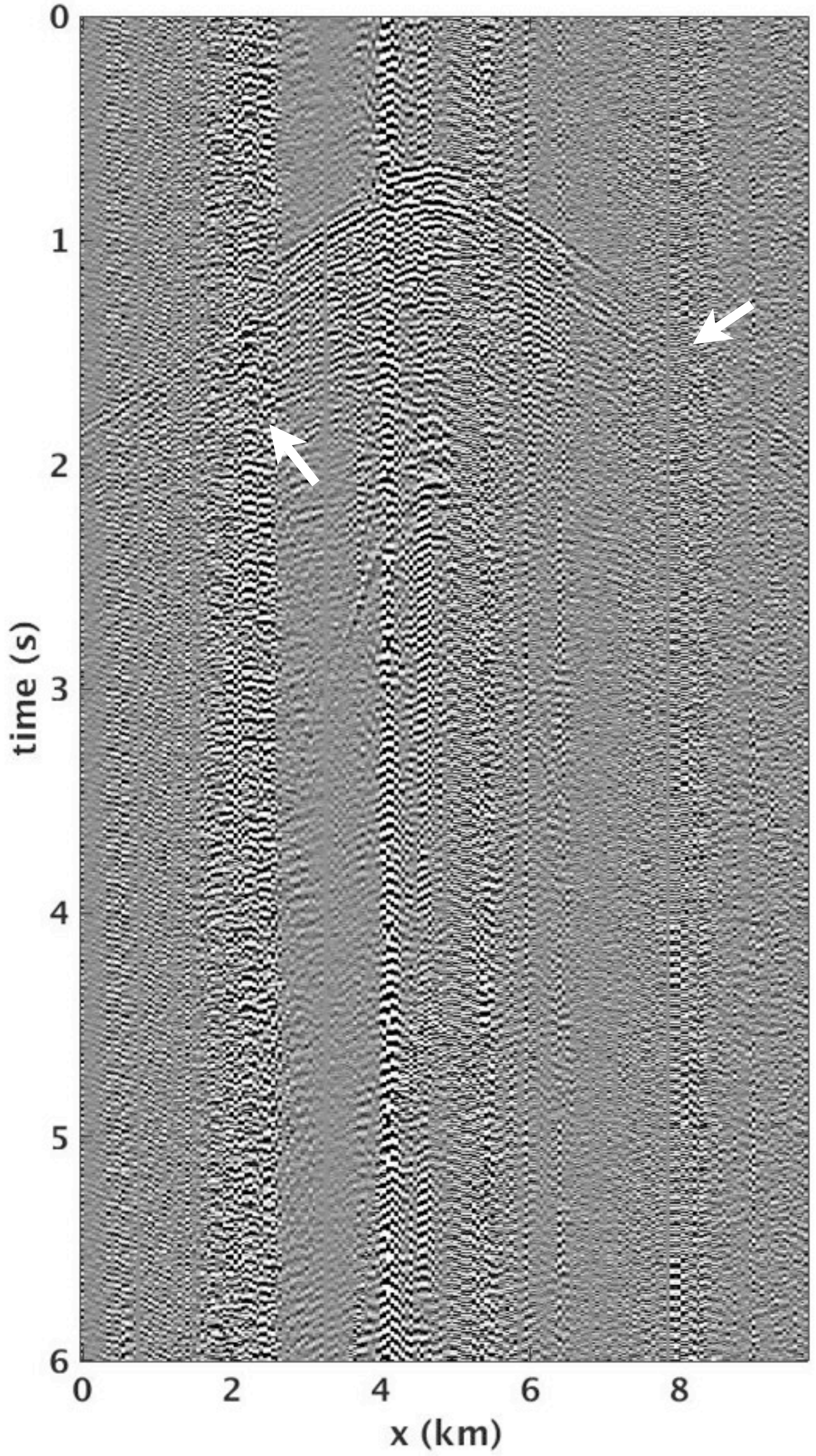
Solve RPCA on each of these matrices independently to separate the low-rank noise from the sparse component

Insert the separated curvelet coefficients for each scale back into the corresponding parabolic angular wedges

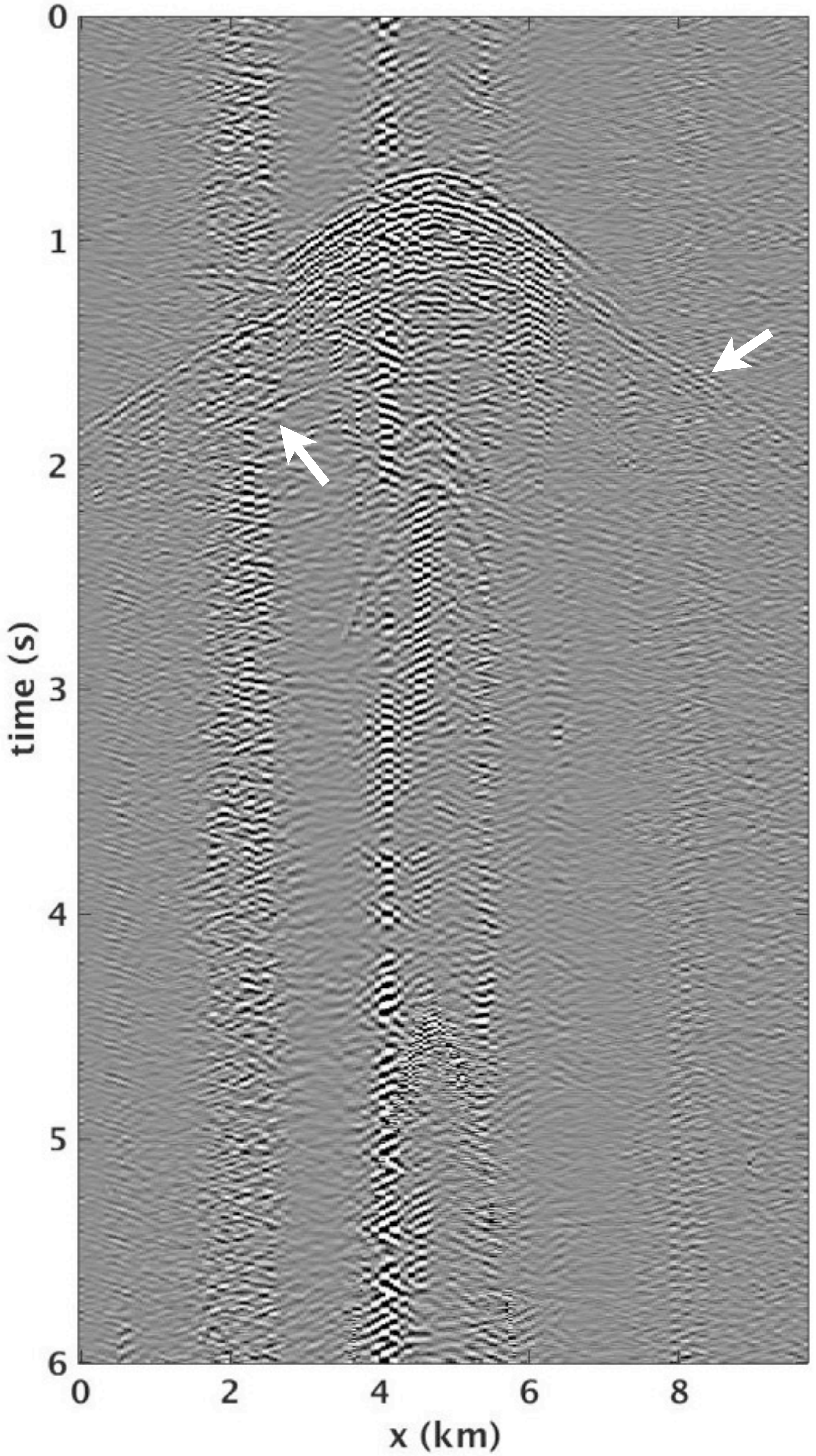
Perform 2D inverse curvelet transform to get estimates for shot records for the separated components

# Curvelet based PCP

True

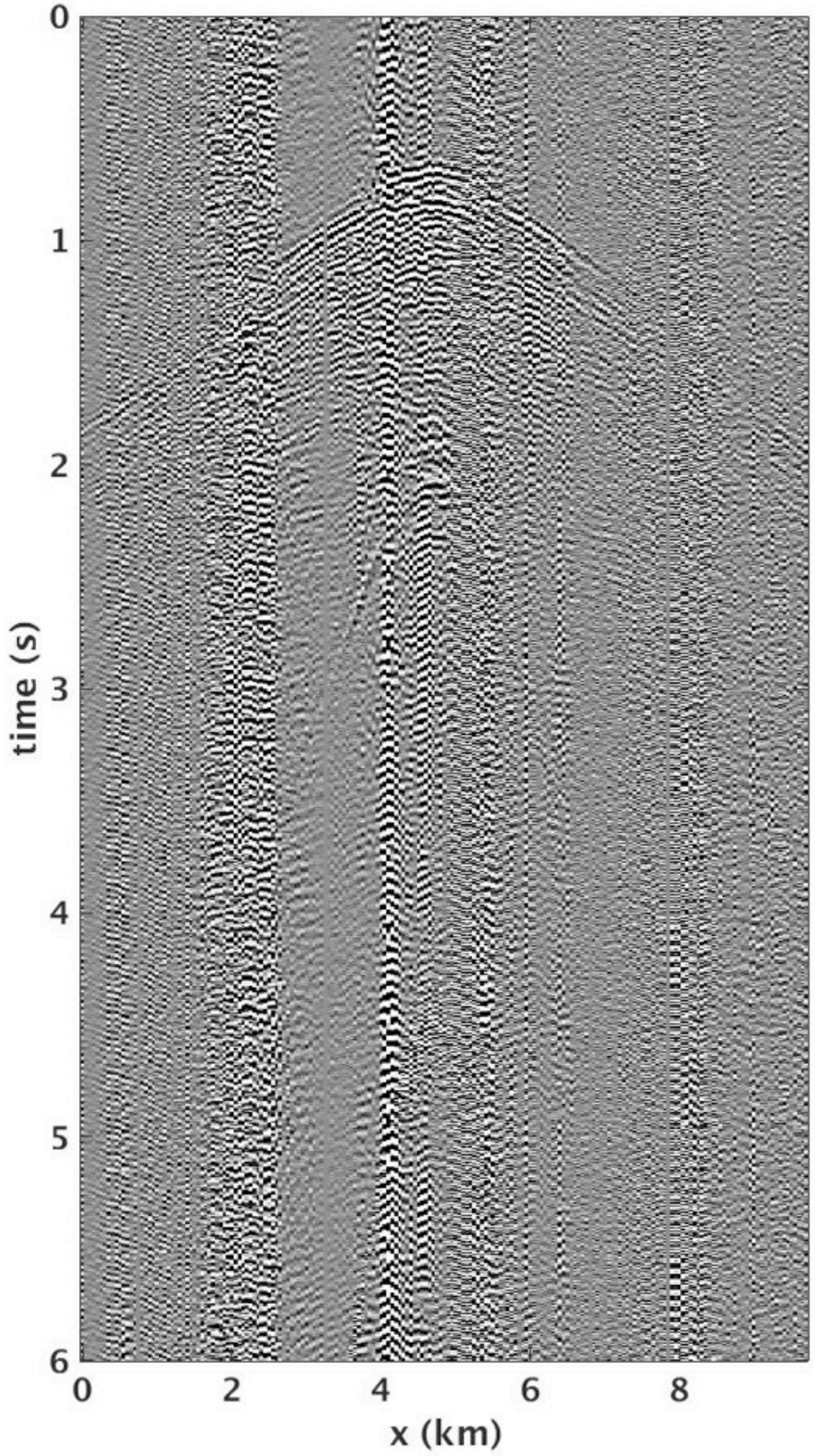



Denoised

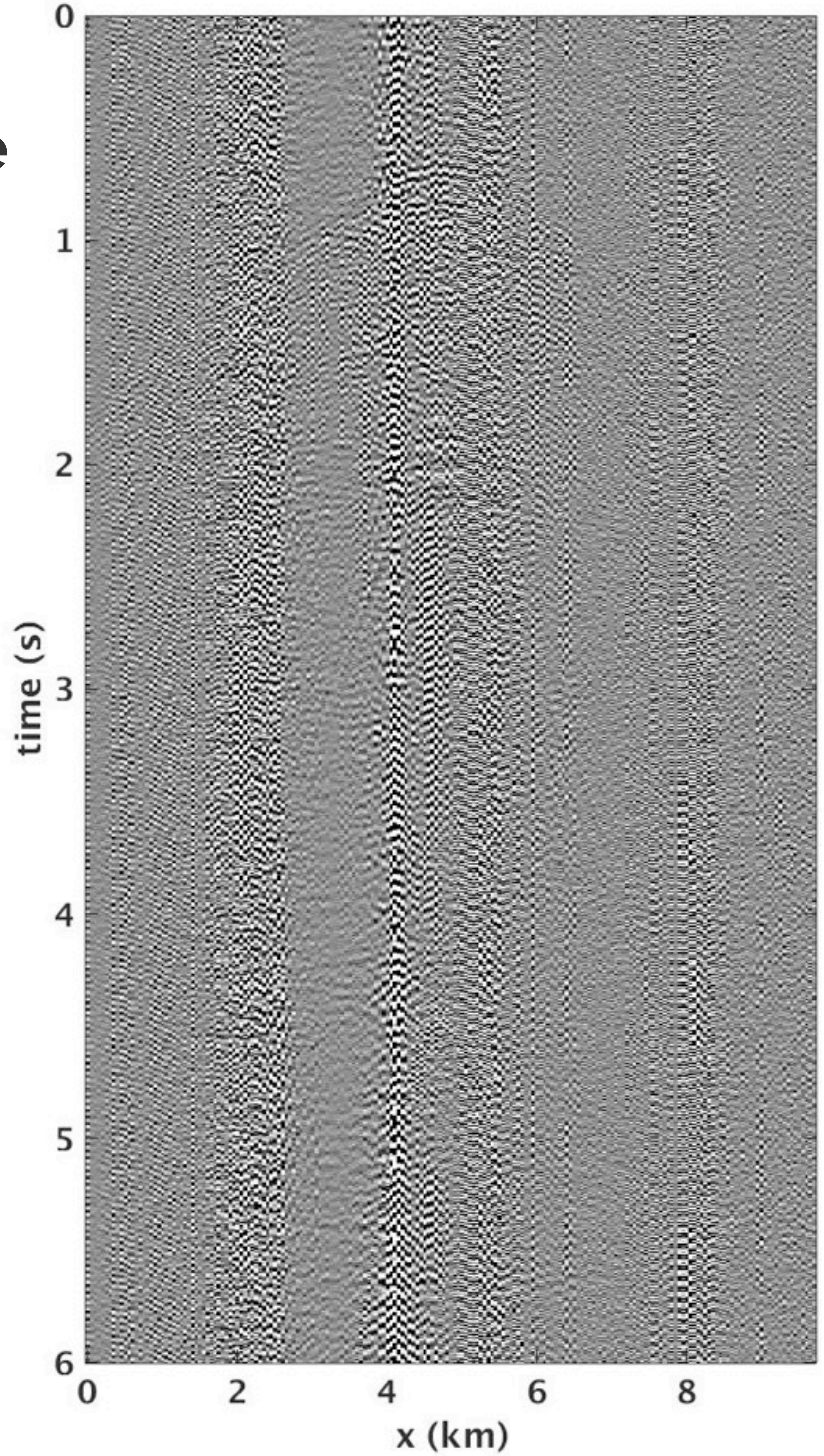


# Curvelet based PCP

True




Difference



## Future directions

Perform noise attenuation on field data before cross-correlation

Use robust-norm to minimize residual noise during inversion process

Re-design acquisition with more randomness across sources and receivers positions

Test random sweep encoding

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# Acknowledgements

This research was carried out as part of the SINBAD project with the support of the member organizations of the SINBAD Consortium.

SINBAD

Thank you for your attention