Source separation via SVD-free rank-minimization in the hierarchical semi-separable representation

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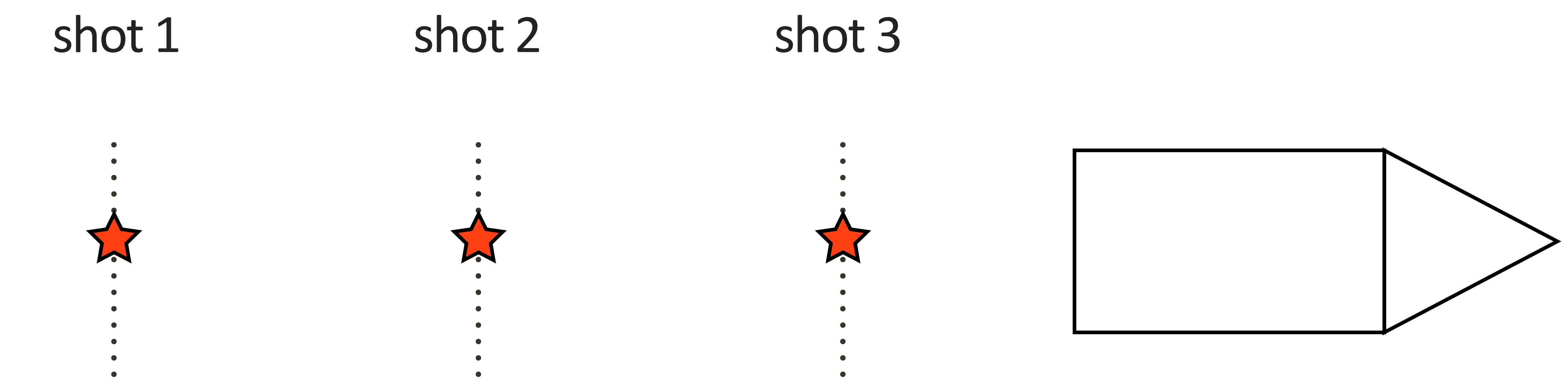
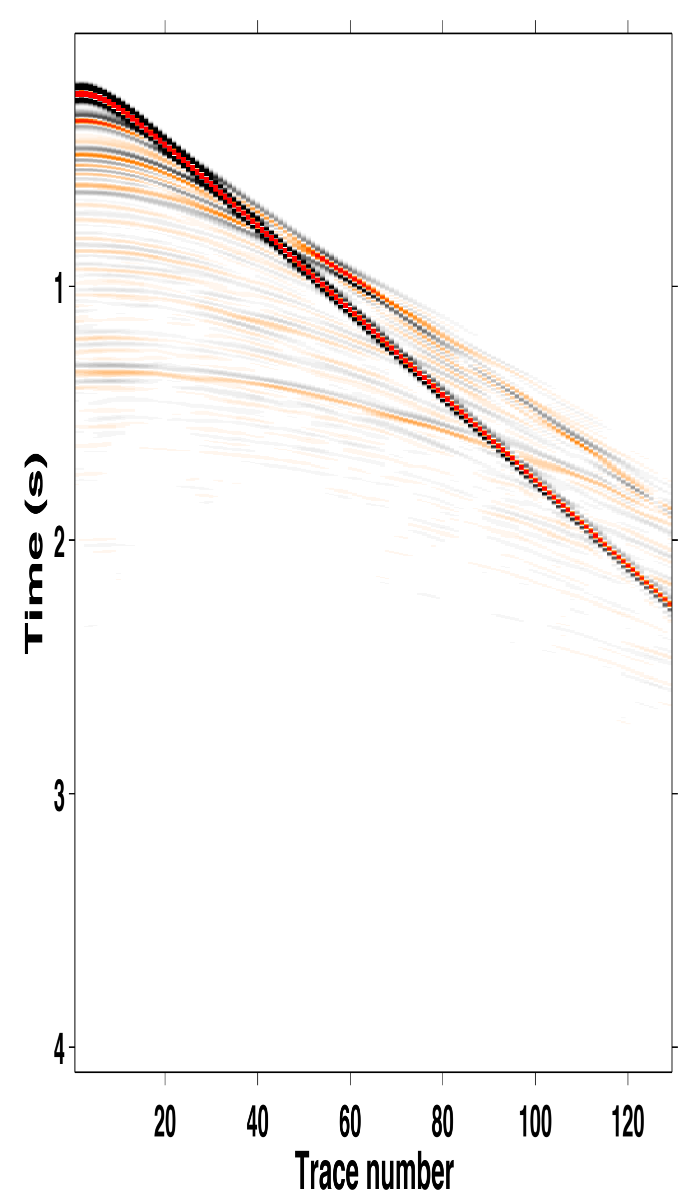
Conventional marine acquisition

source depth = 10 m

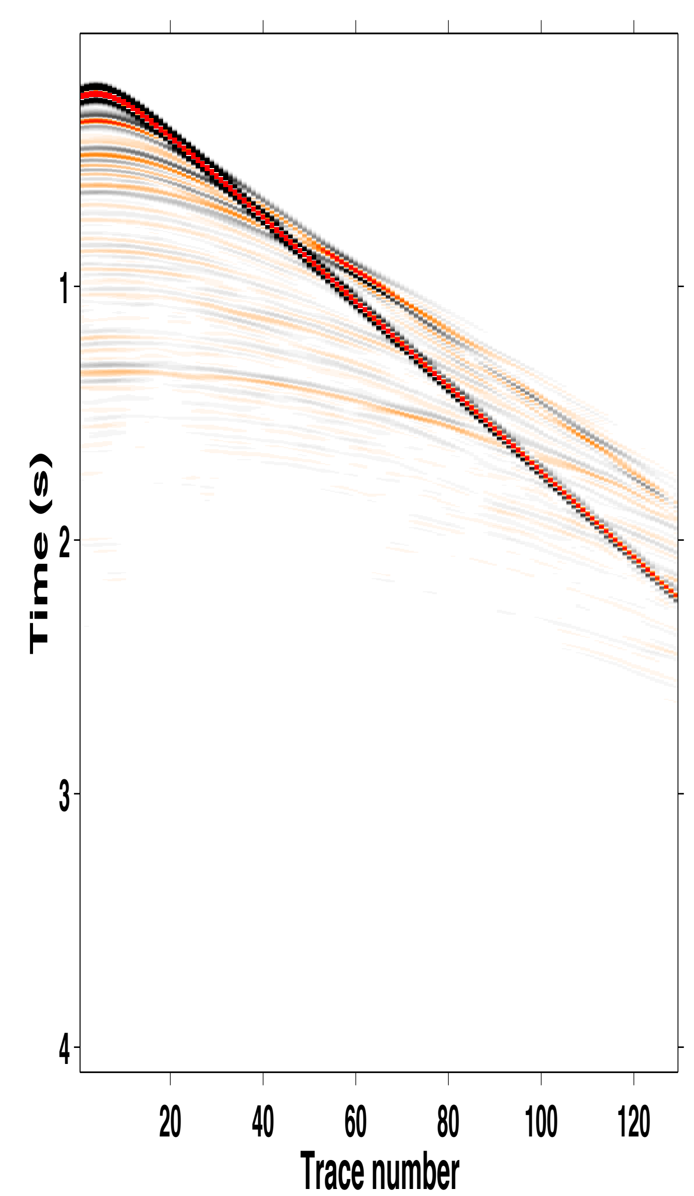
regularly sampled spatial grid →



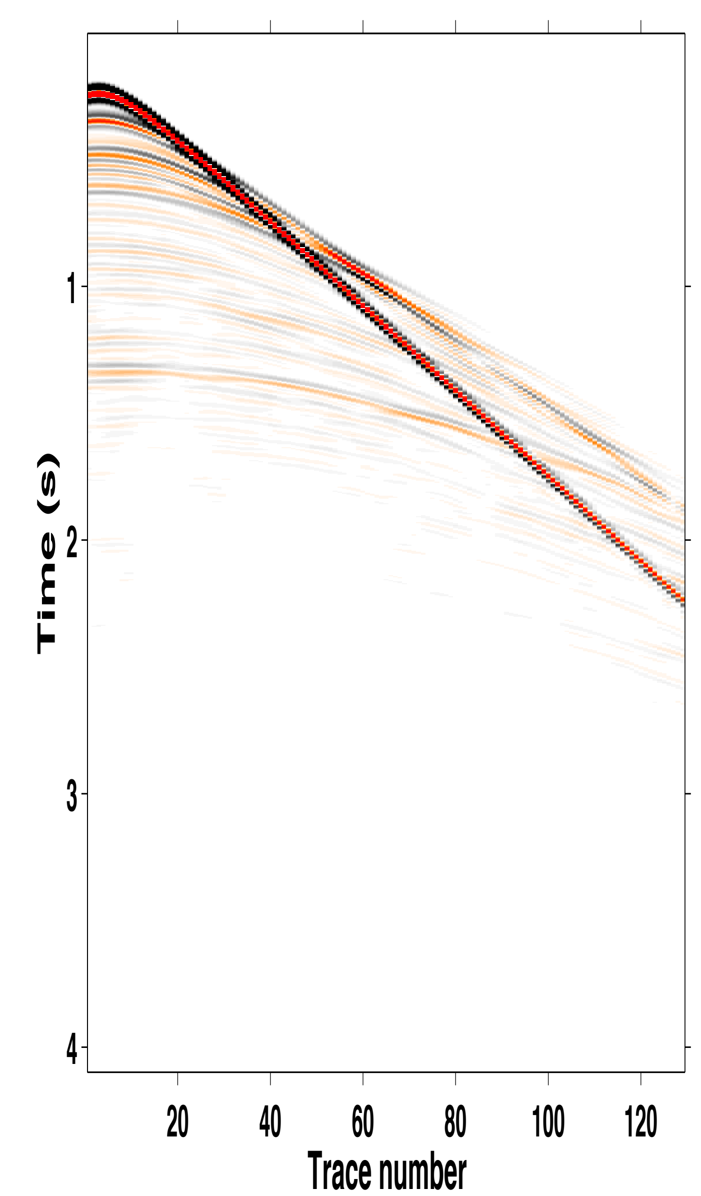
shot 1



shot 2

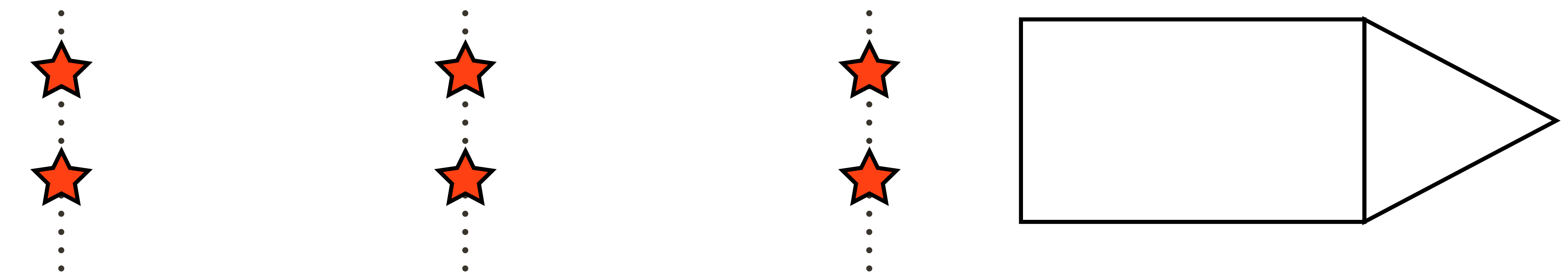


shot 3



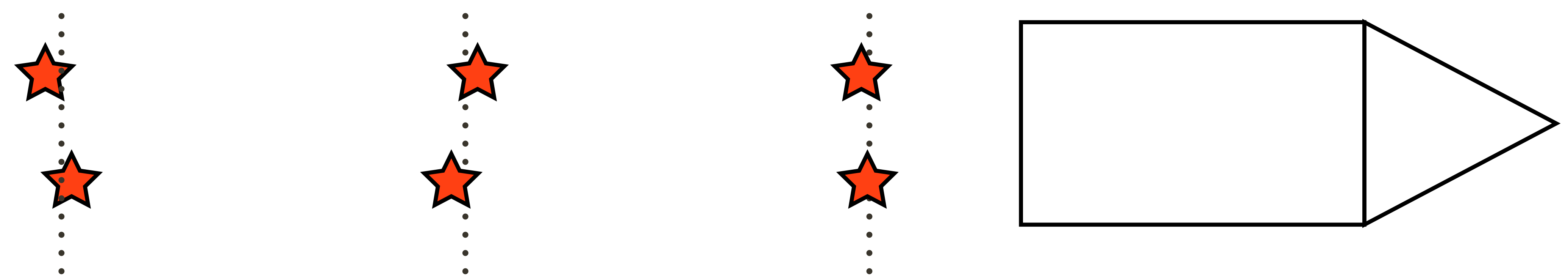
Blended/Simultaneous marine acquisition

regularly sampled spatial grid



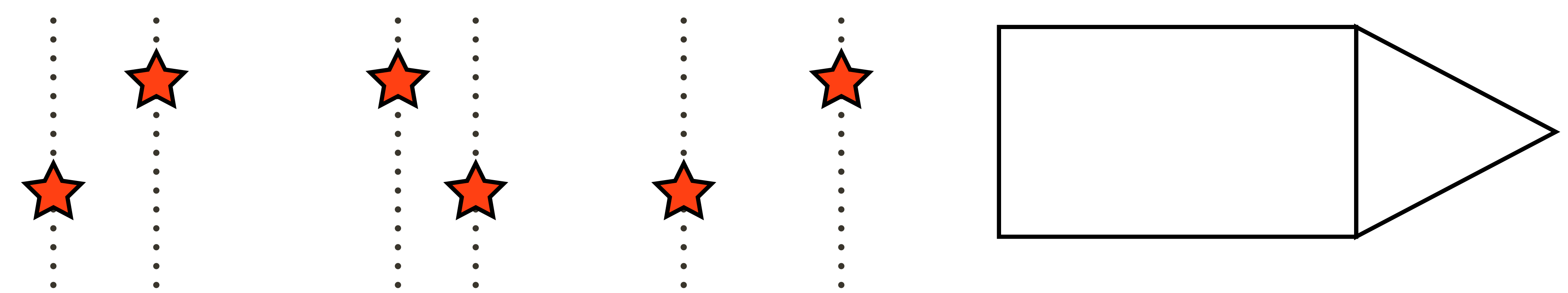
almost regularly sampled spatial grid

(over/under acquisition)



irregularly sampled spatial grid

(*Time-jittered* acquisition)



[Wason and Herrmann, 2013]
[Mansour et. al., 2012]

Blended/Simultaneous marine acquisition

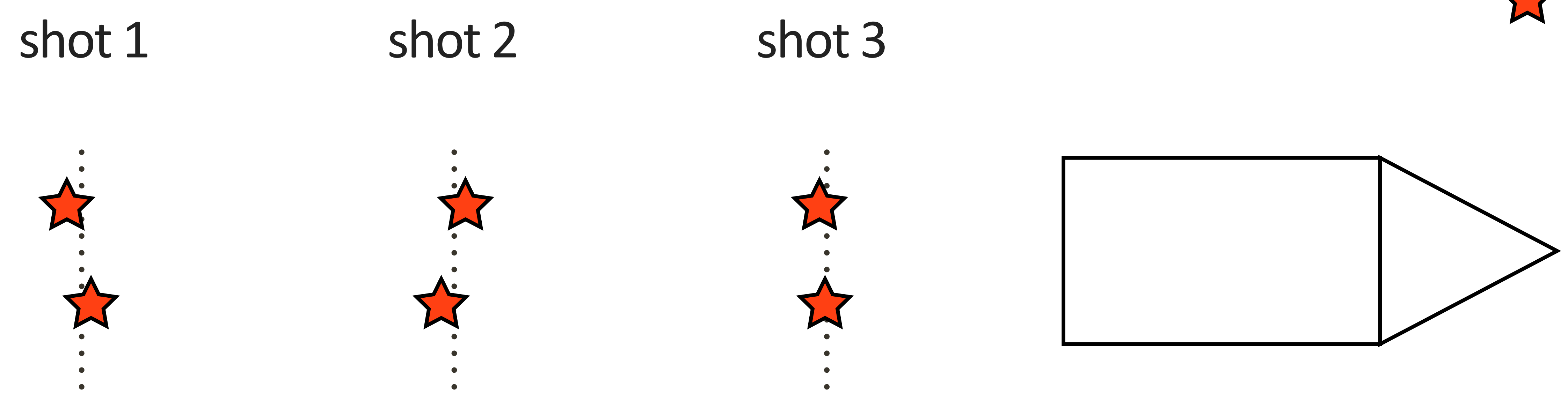
[over/under acquisition]

★ source1 depth = 10 m

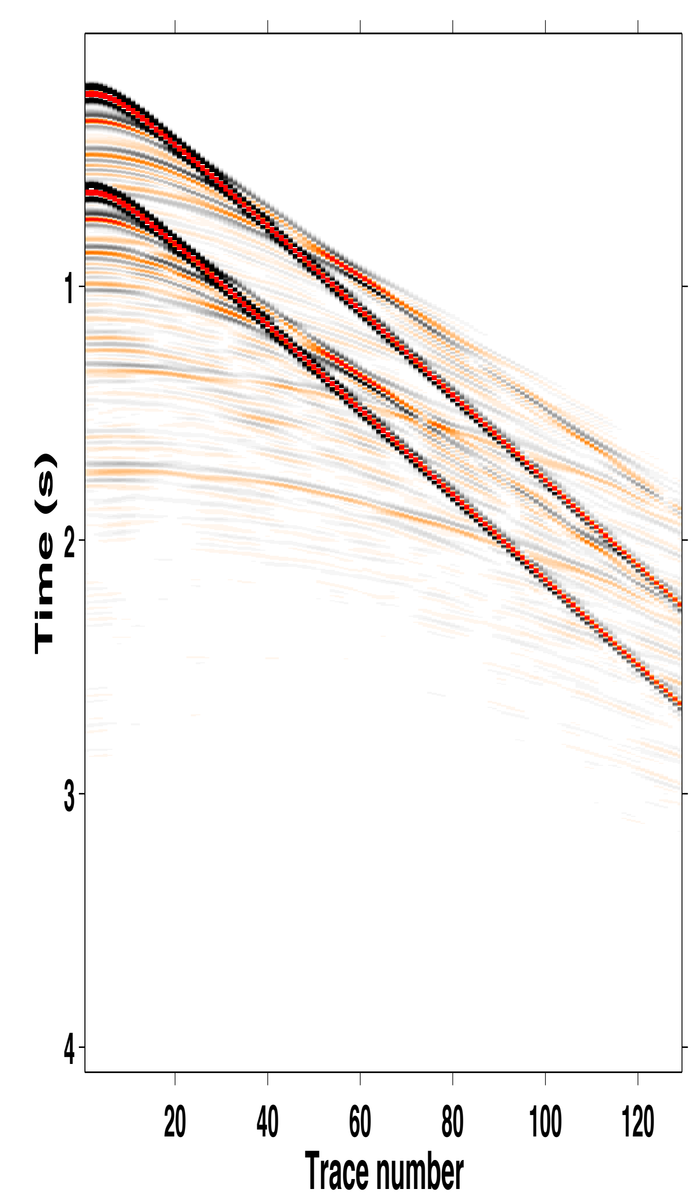
★ source2 depth = 15 m

regularly sampled spatial grid
(almost)

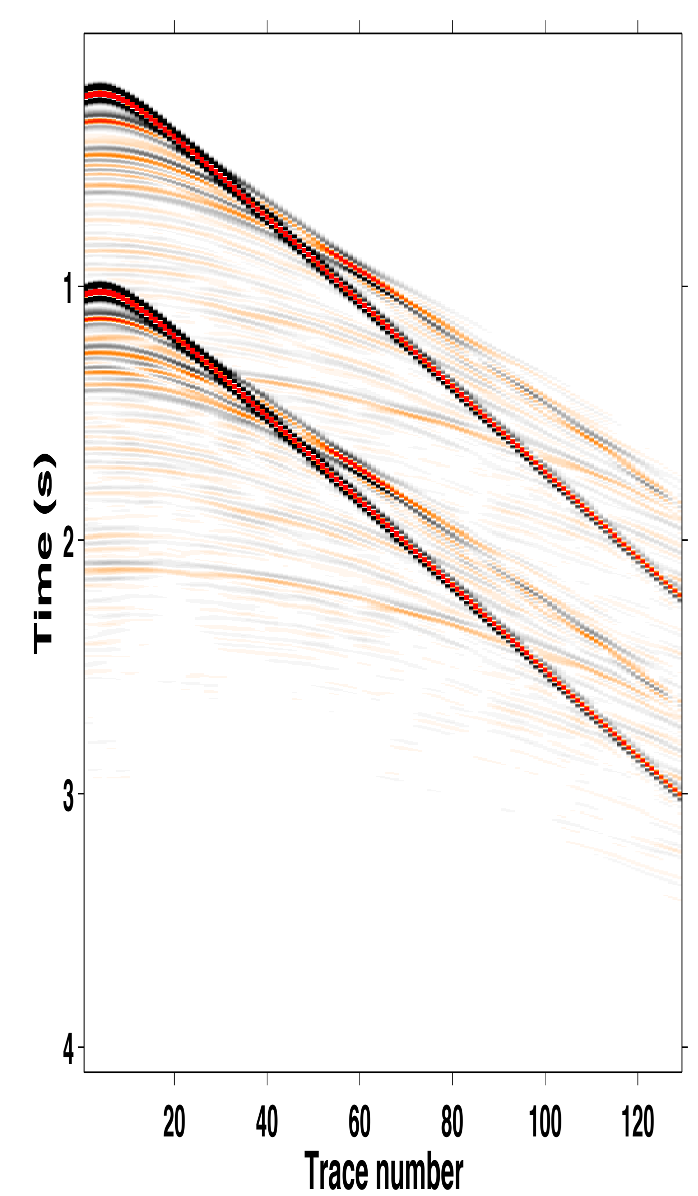
shot-time randomness - ***LOW***



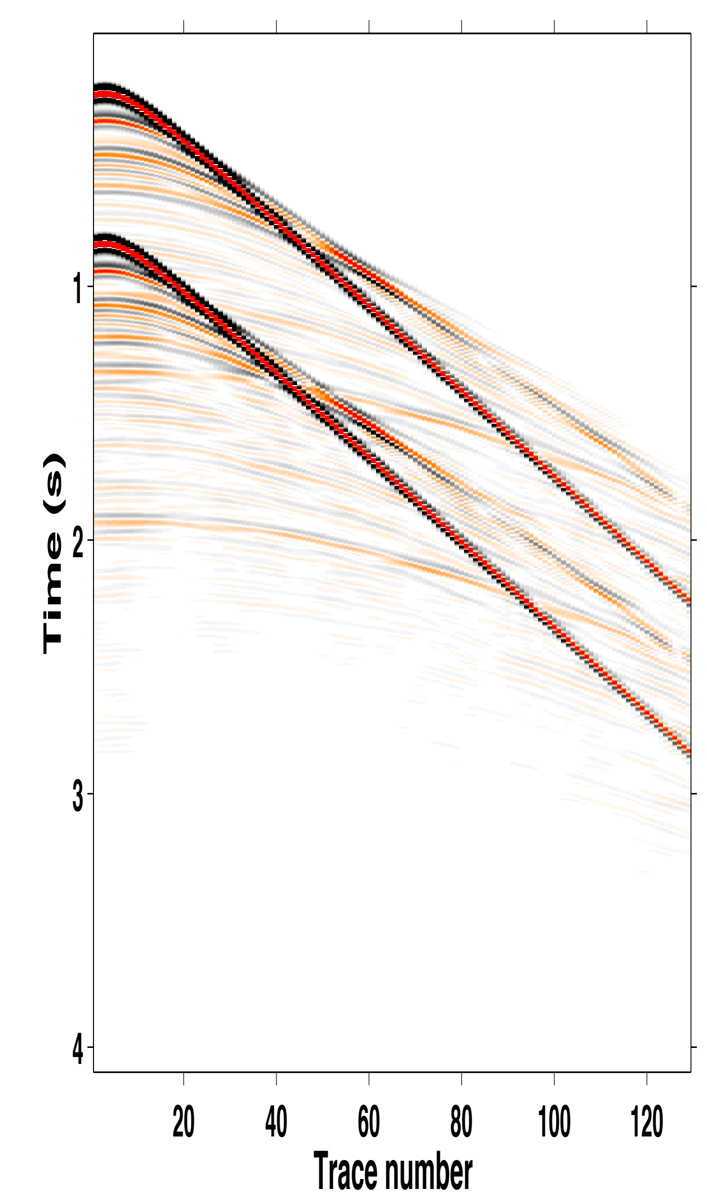
shot 1



shot 2



shot 3



Challenges

- Source separation (or *deblending*)
  - recover individual datasets

- Shot-time randomness
  - low

[Candès and Donoho, 2000; Herrmann, 2008]

Compressed sensing

Successful sampling & reconstruction scheme

- exploit *structure* via *sparsifying* transform
  - *fast decay* of "transform domain" coefficients
- sampling
  - randomly blended data *decreases* sparsity in "transform domain"
- optimization
  - via *sparsity-promotion*

[Candès and Plan, 2010, Oropeza and Sacchi, 2011]

SLIM

Matrix completion

Successful reconstruction scheme

- exploit *structure*
  - *low-rank / fast decay* of singular values
- sampling
  - randomly blended data *increases* rank in “transform domain”
- optimization
  - via *rank-minimization (nuclear norm-minimization)*

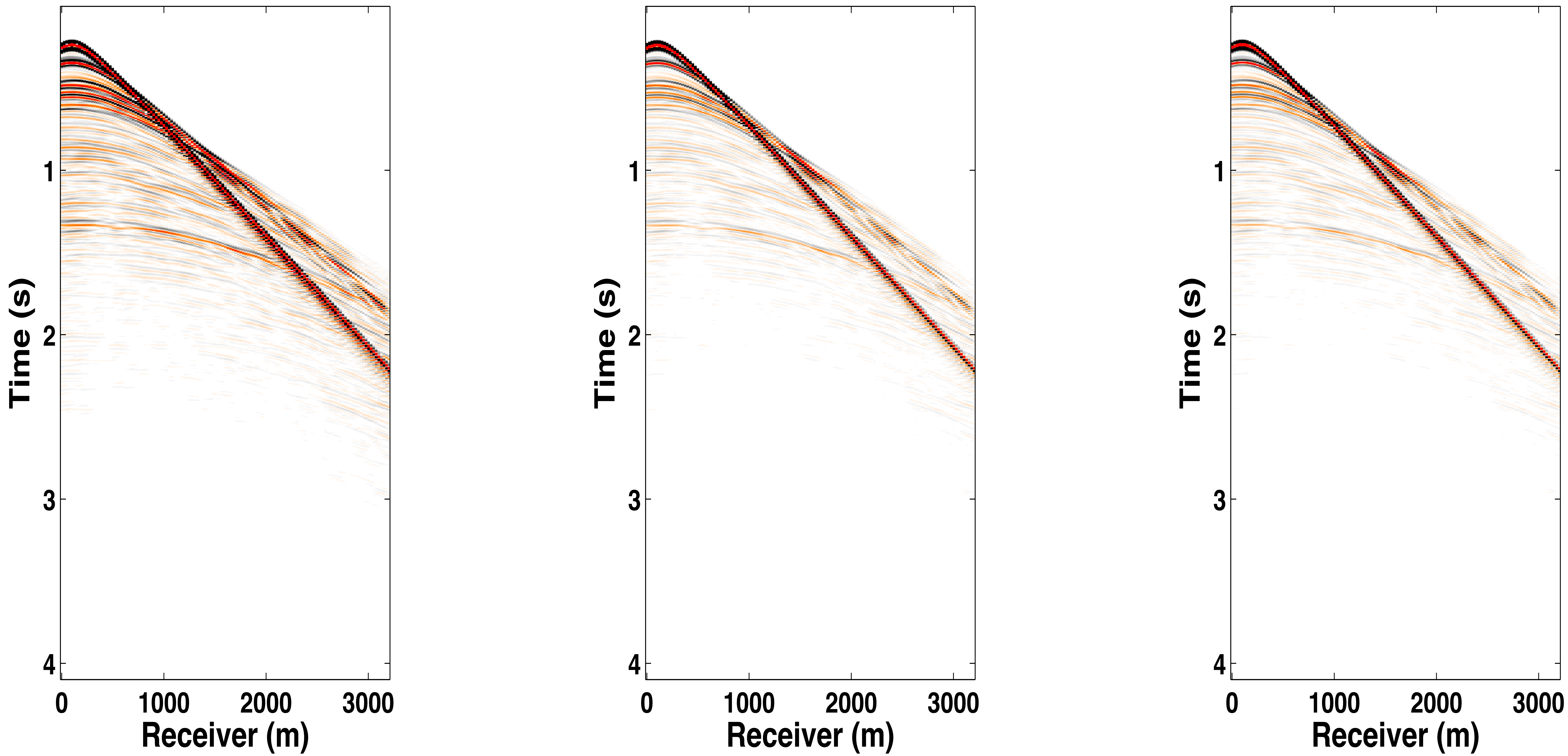
Low-rank structure

In which domain?

source-receiver or *midpoint-offset*

Blended data (w/o delay)

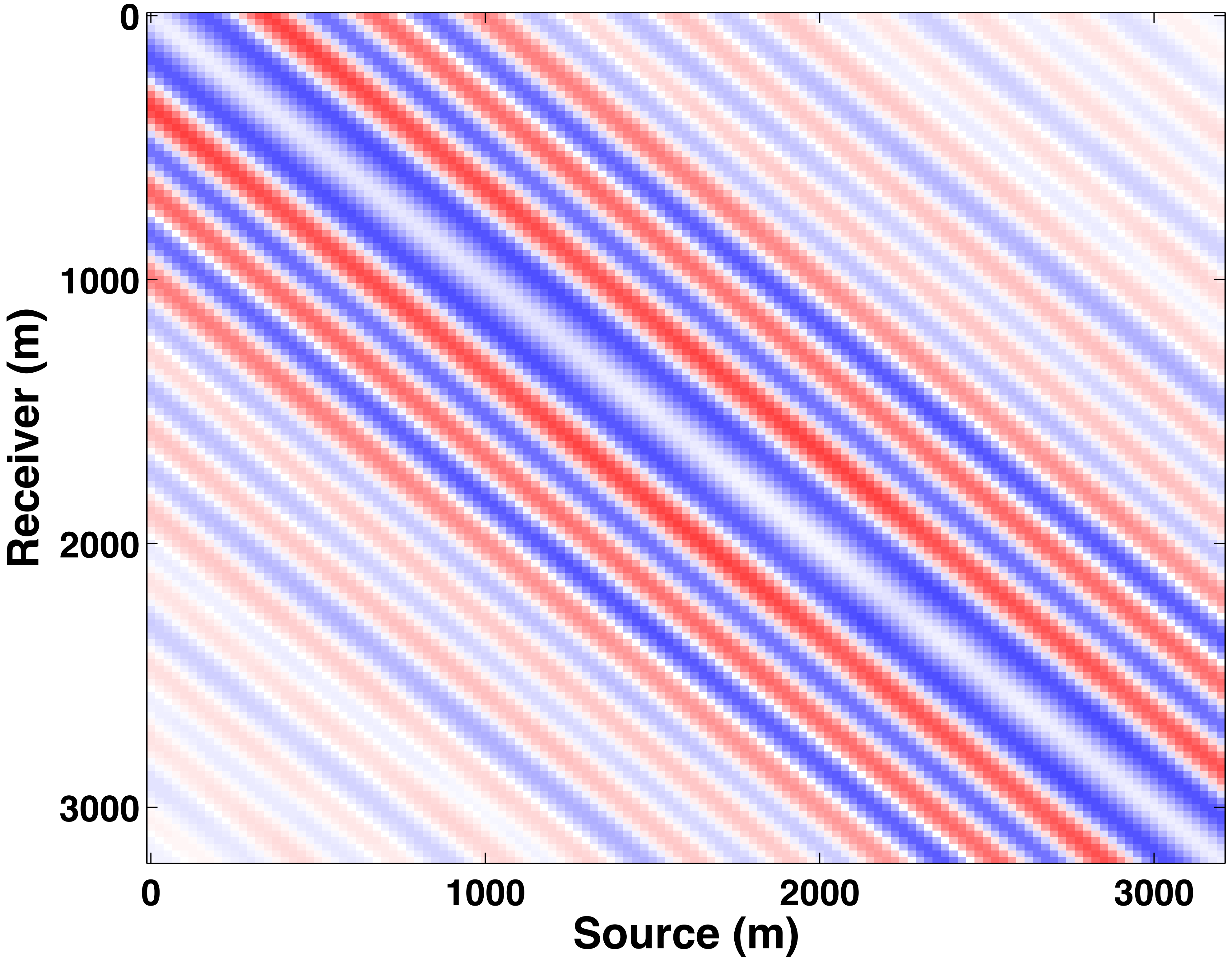
blended shot = source 1 + source 2



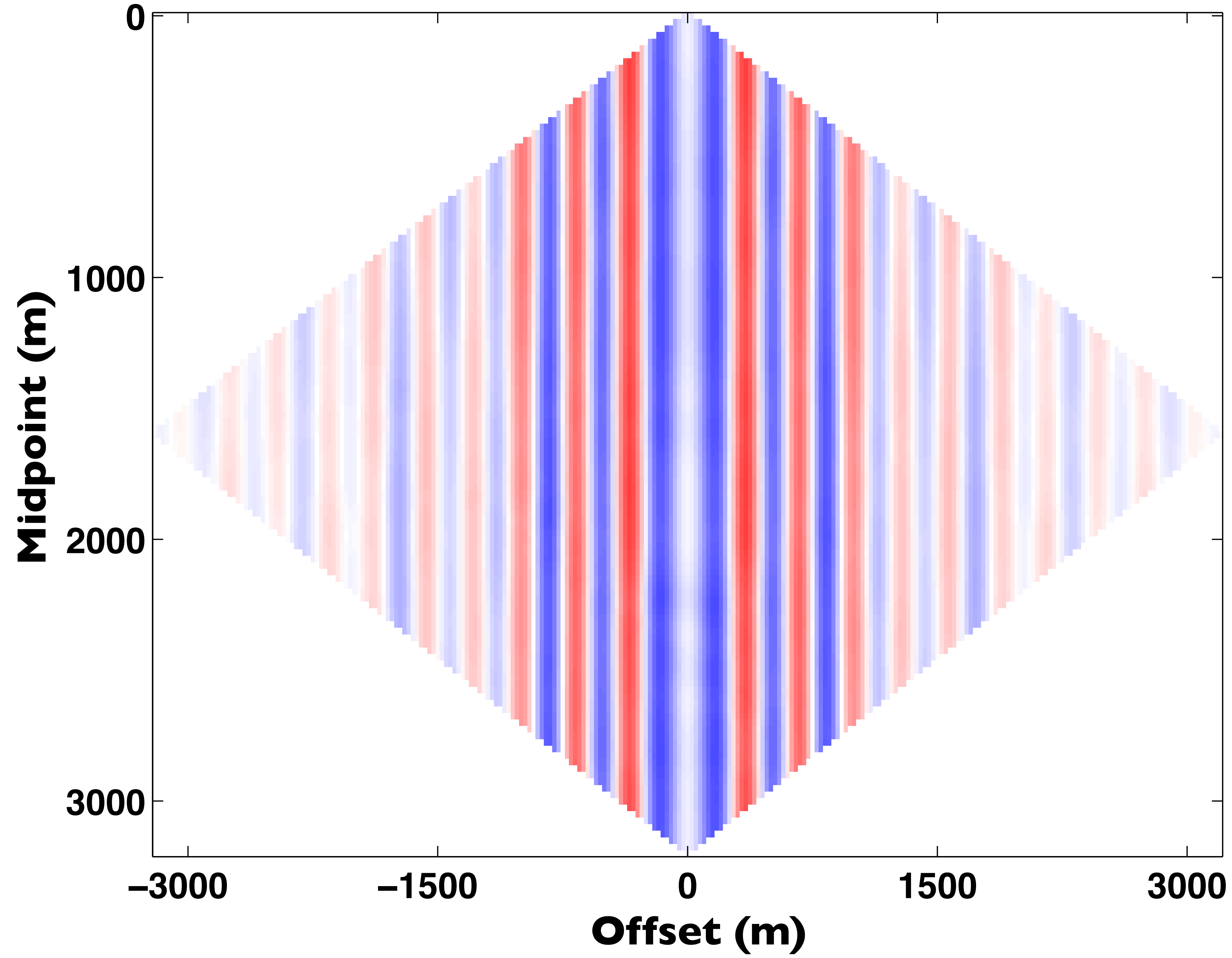
In which domain?

frequency slice at 5 Hz

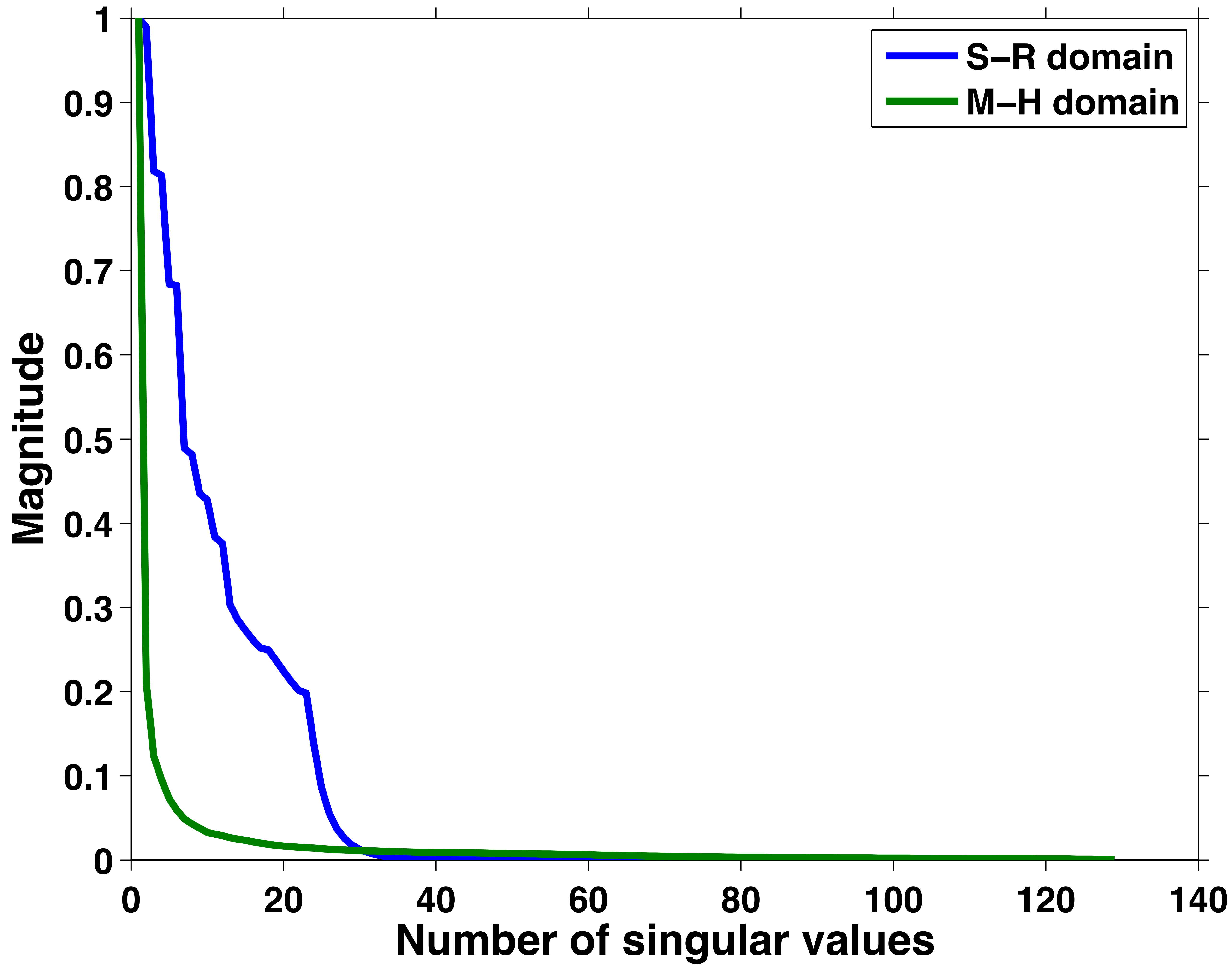
source-receiver domain



midpoint-offset domain



Decay of singular values



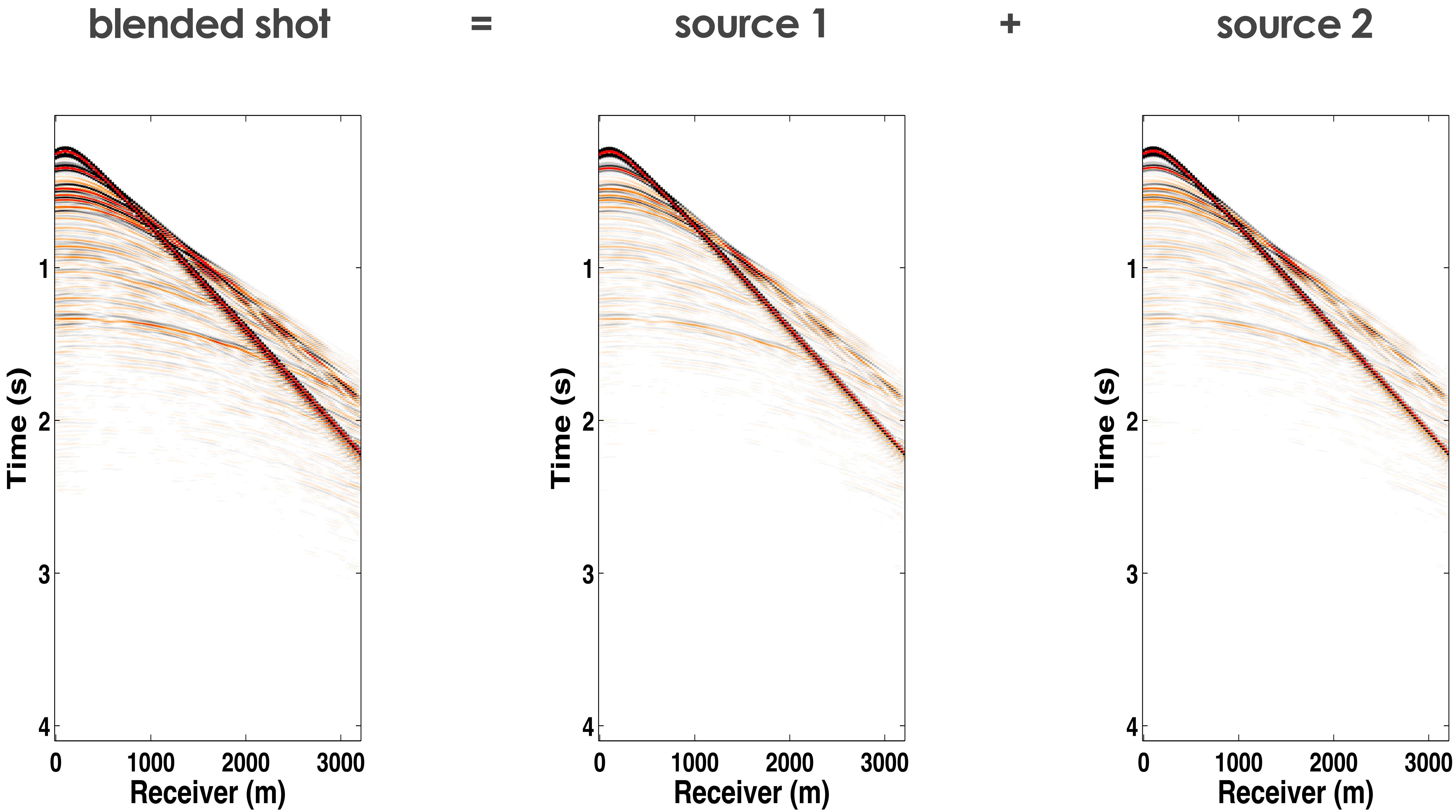
low-rank in midpoint-offset domain

Sampling scheme

sample to *break* the structure

random time delays break the structure

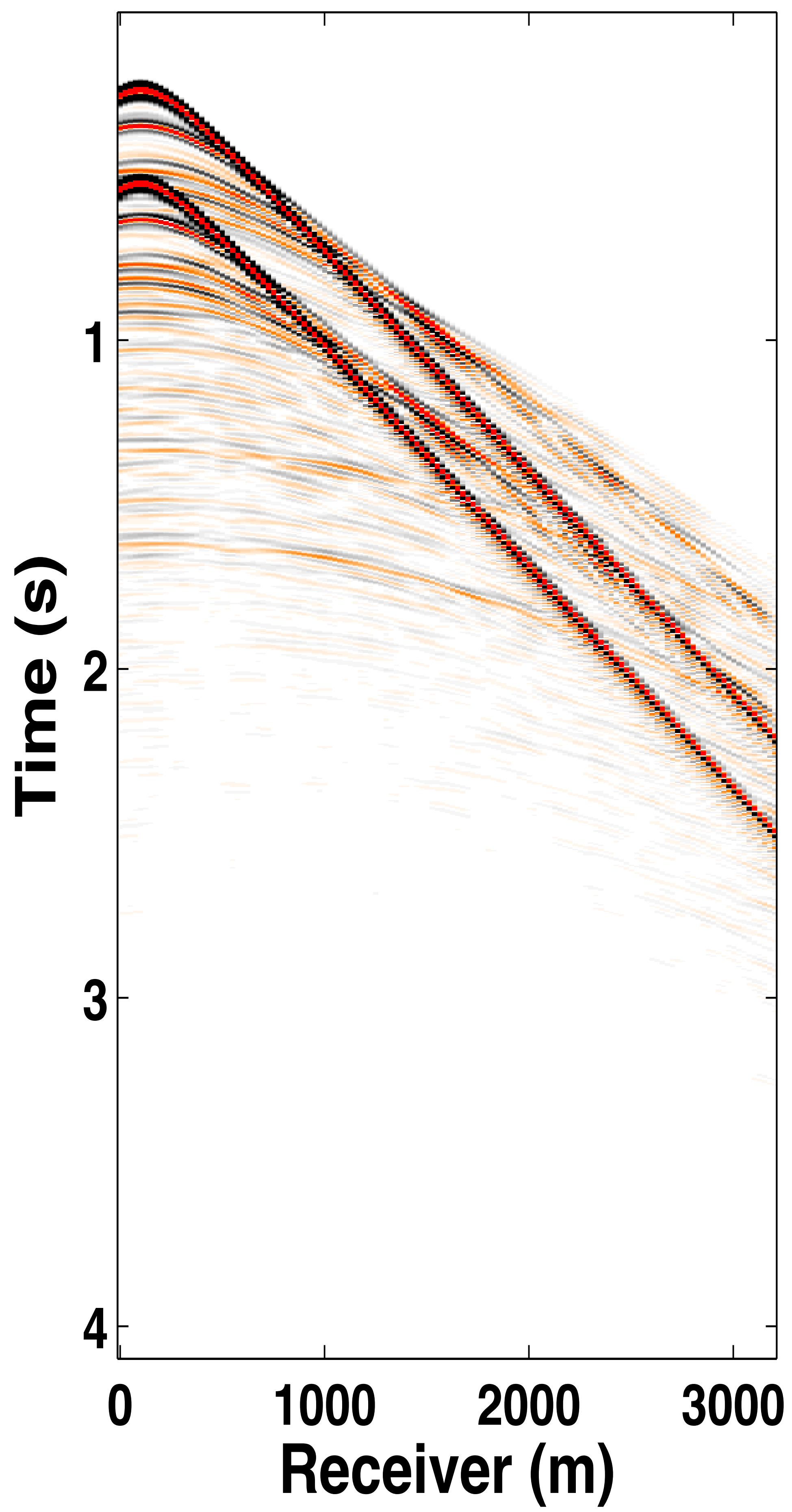
Blended data (w/o delay)

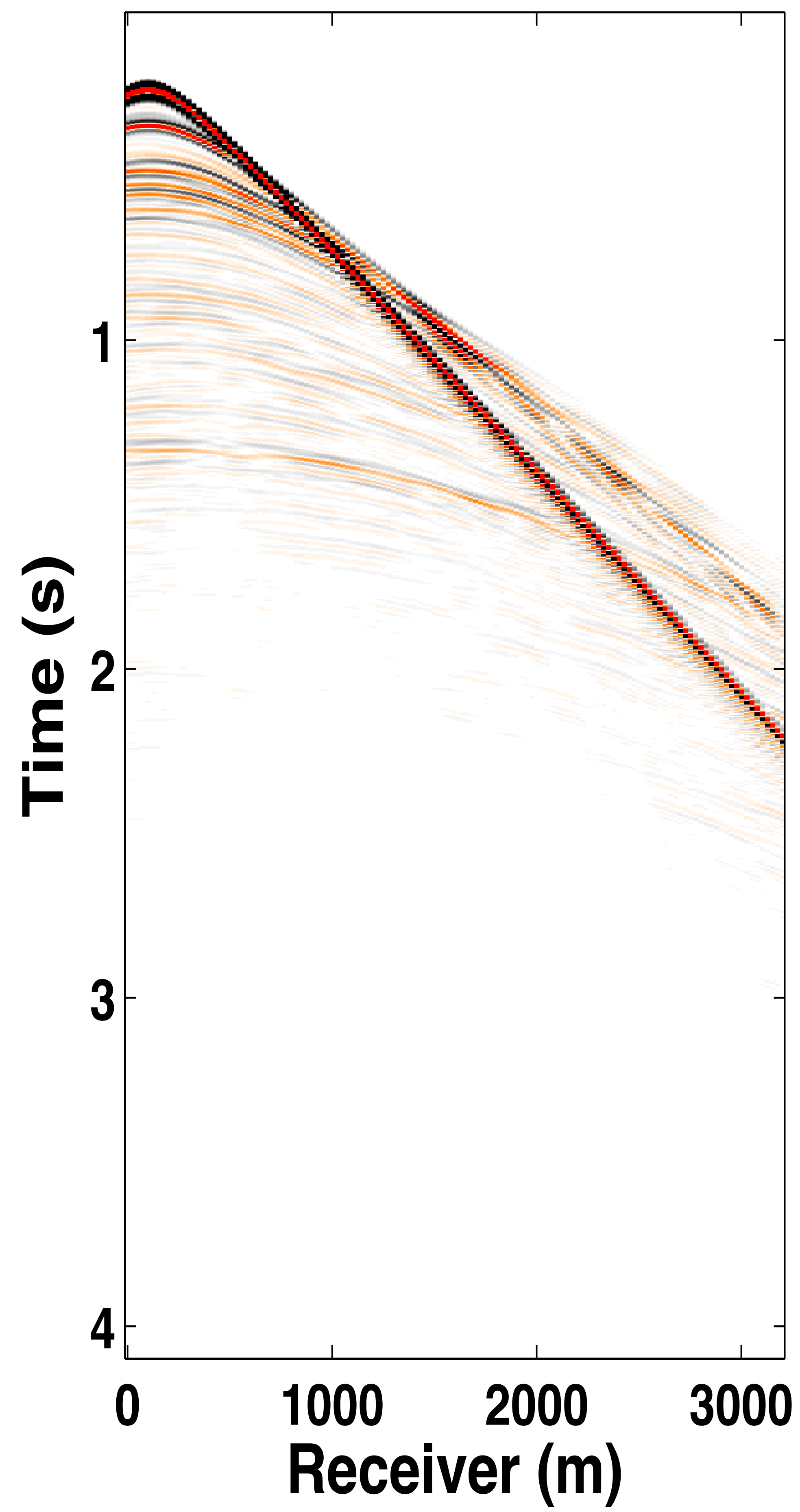


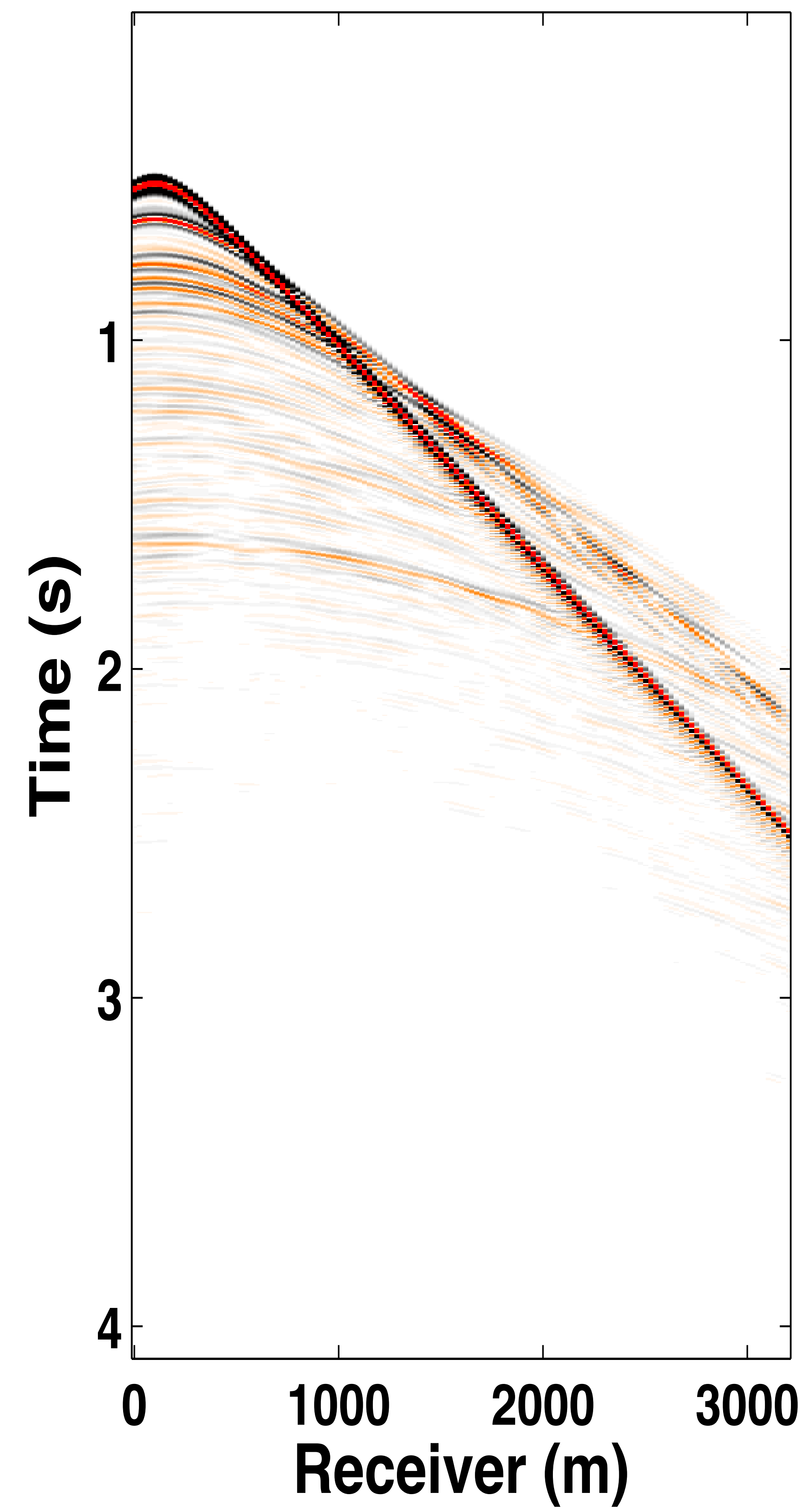
Blended data (w/ delay)

- random time delays applied to source 2

blended shot = **source 1** + **source 2 (time-delayed)**



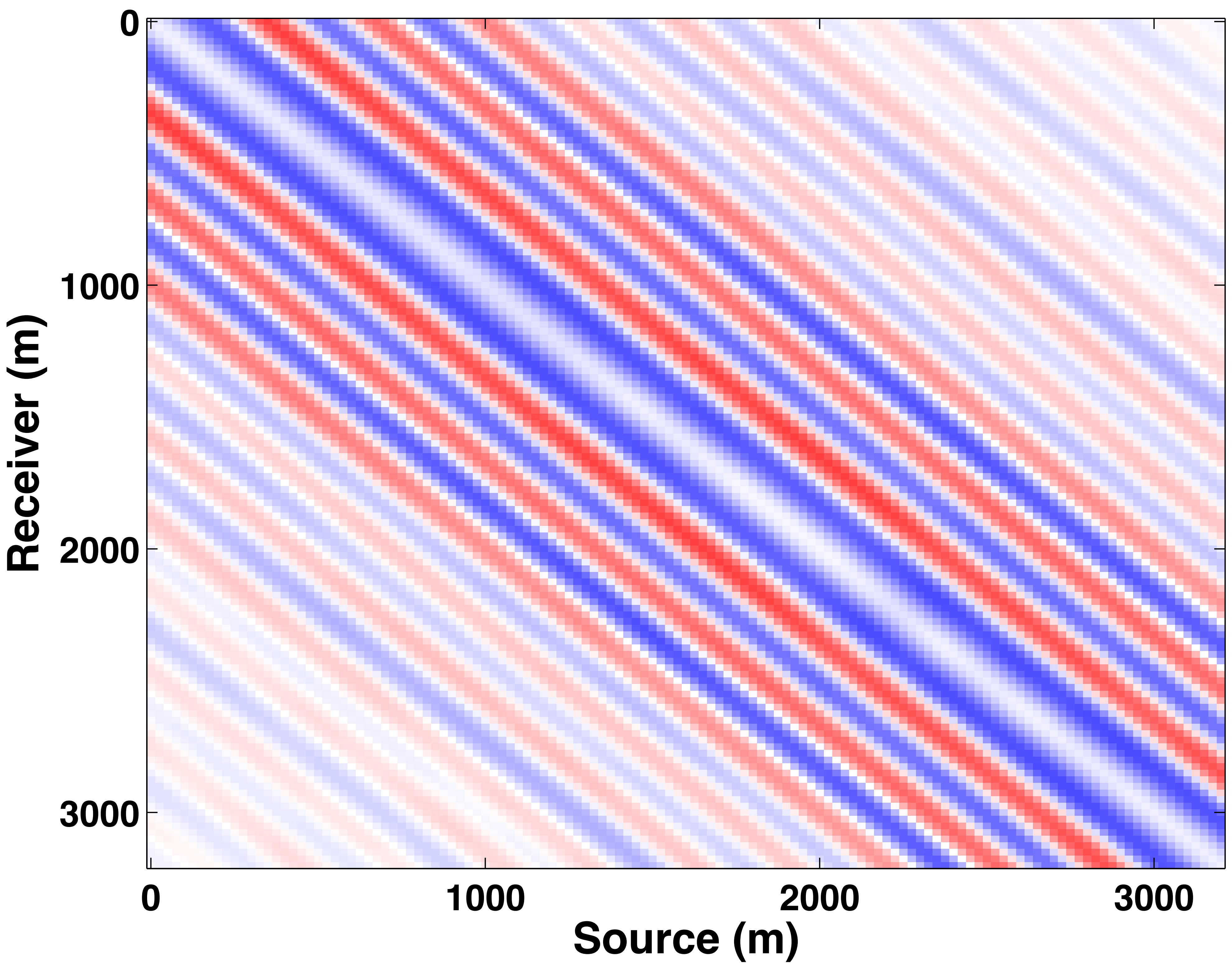




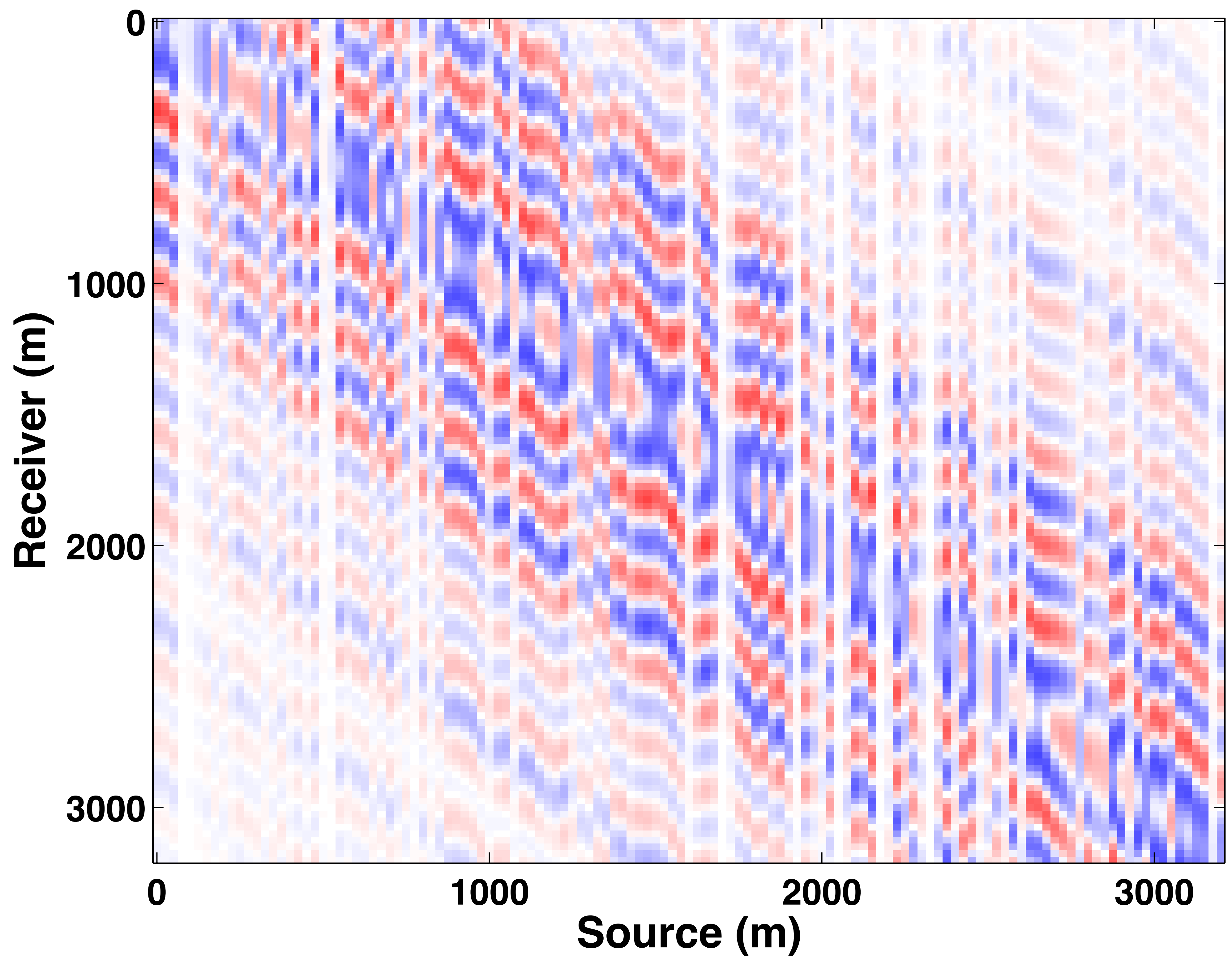
Source-receiver domain

frequency slice at 5 Hz

without delay



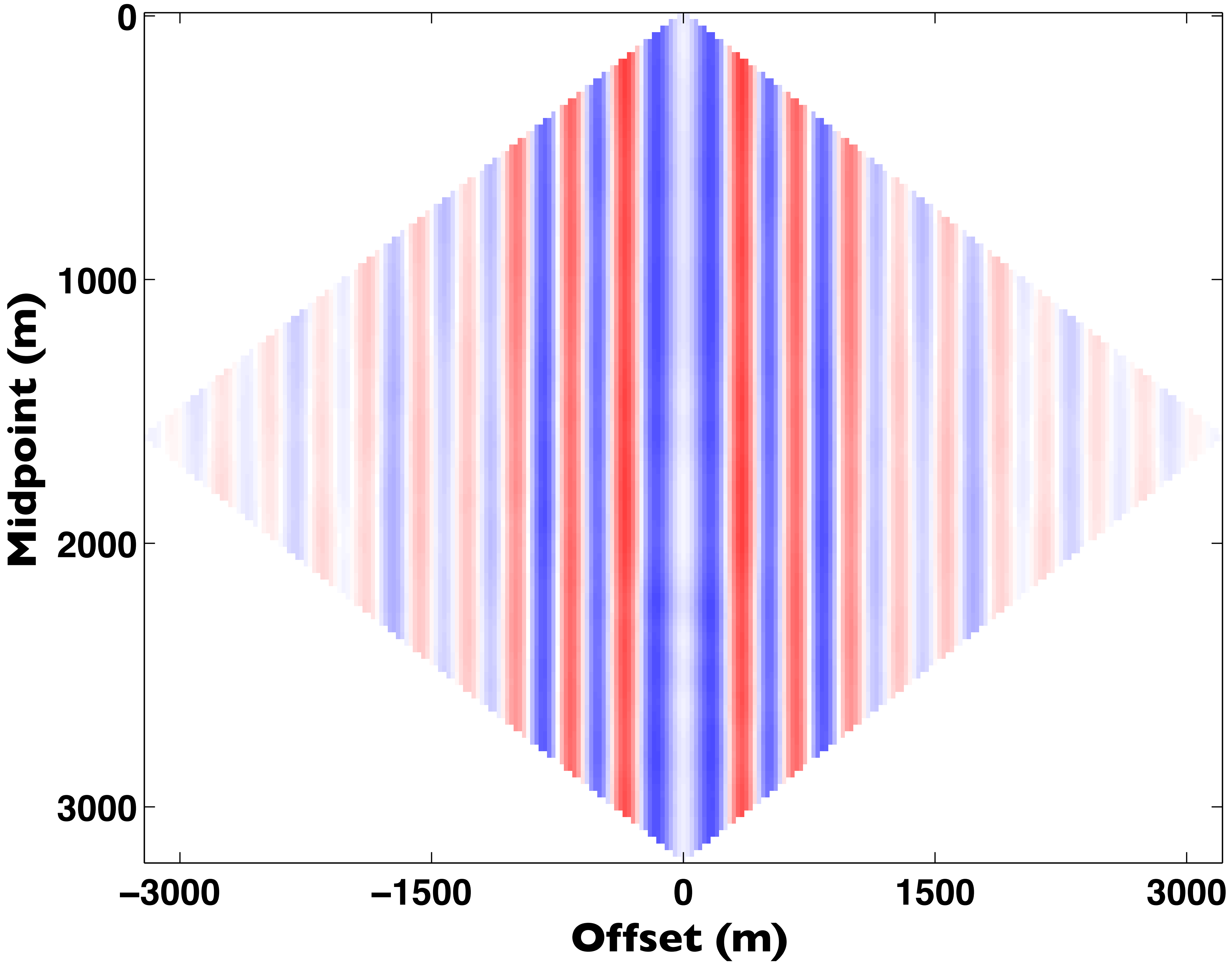
with delay



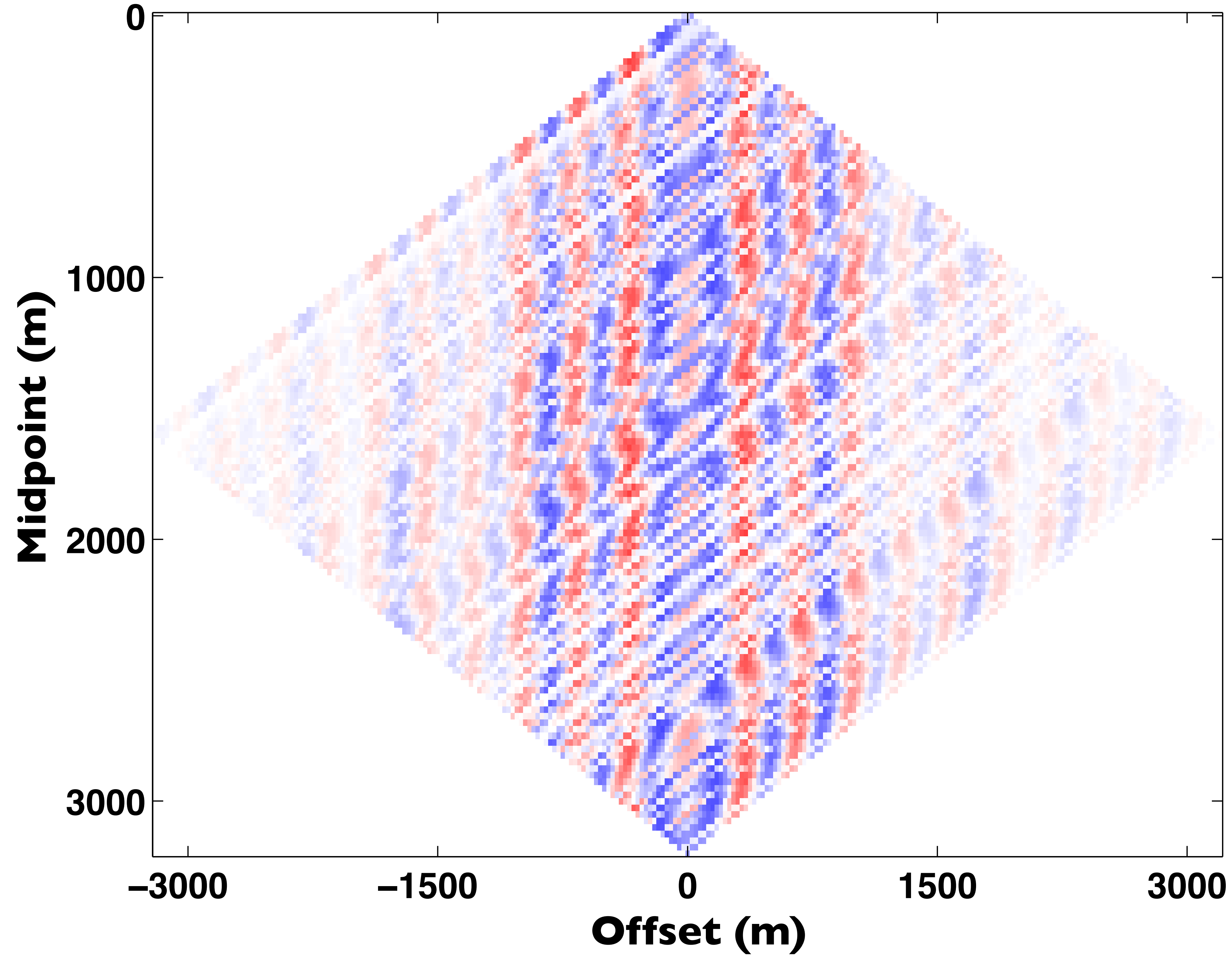
Midpoint-offset domain

frequency slice at 5 Hz

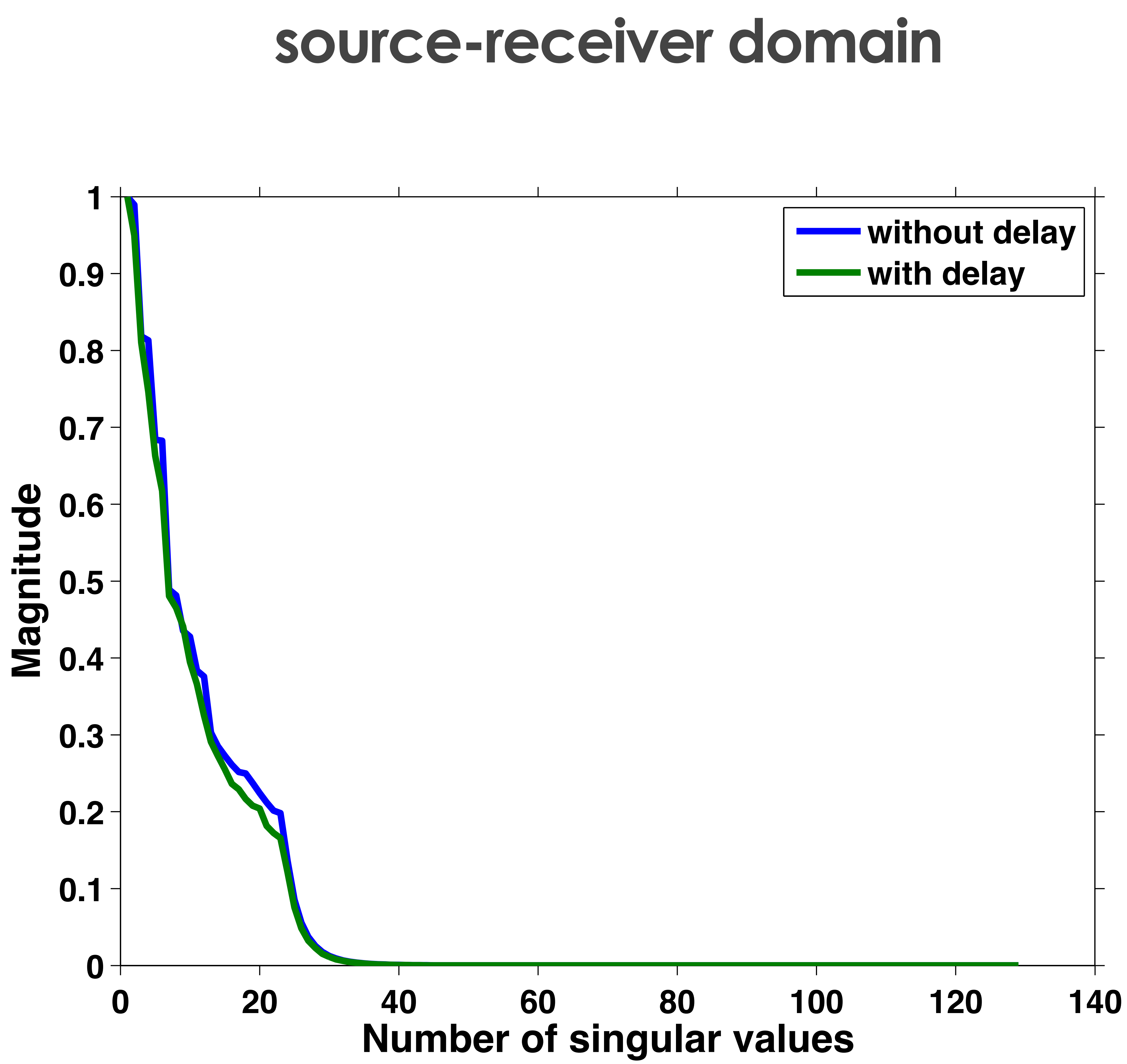
without delay

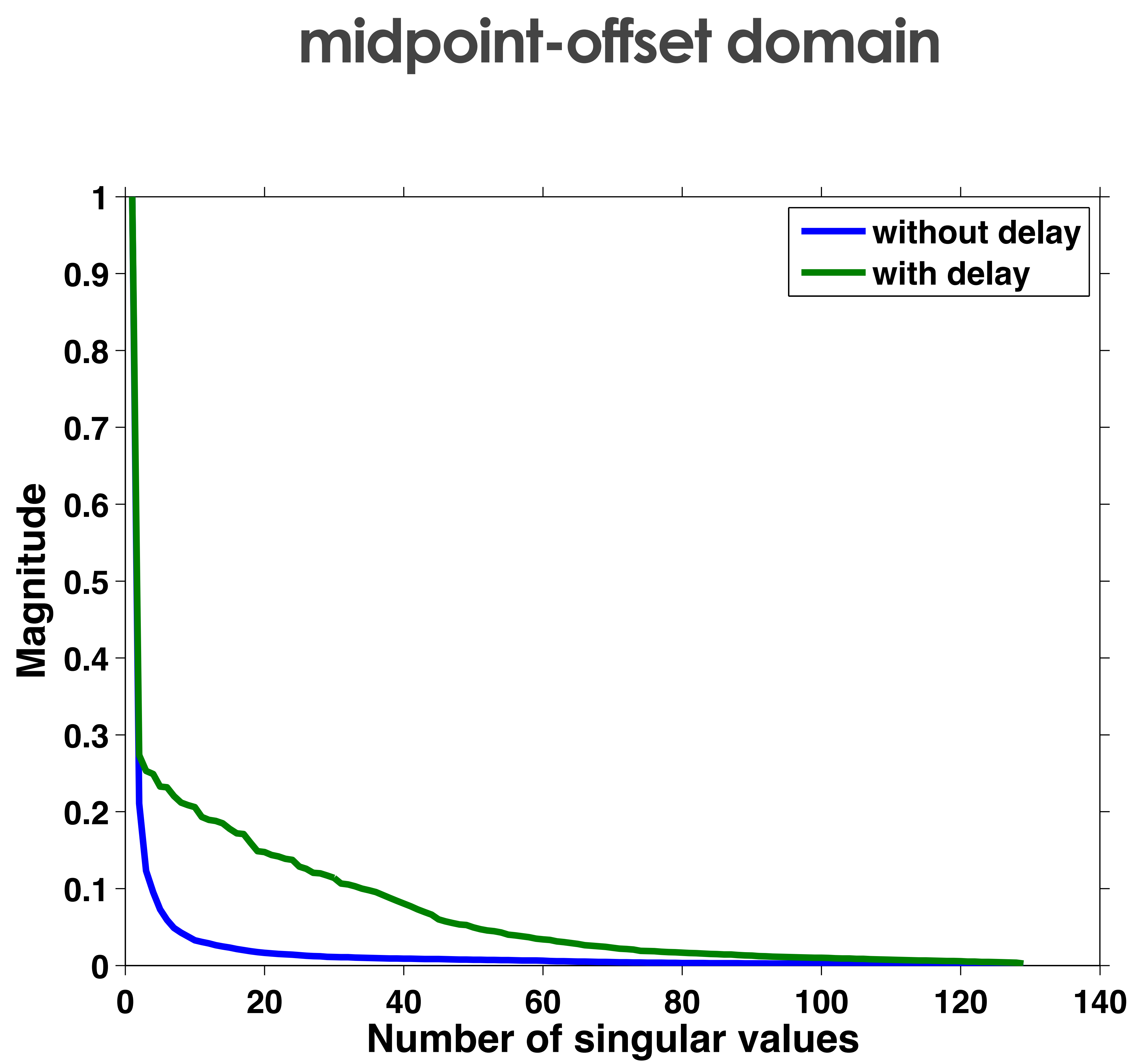


with delay



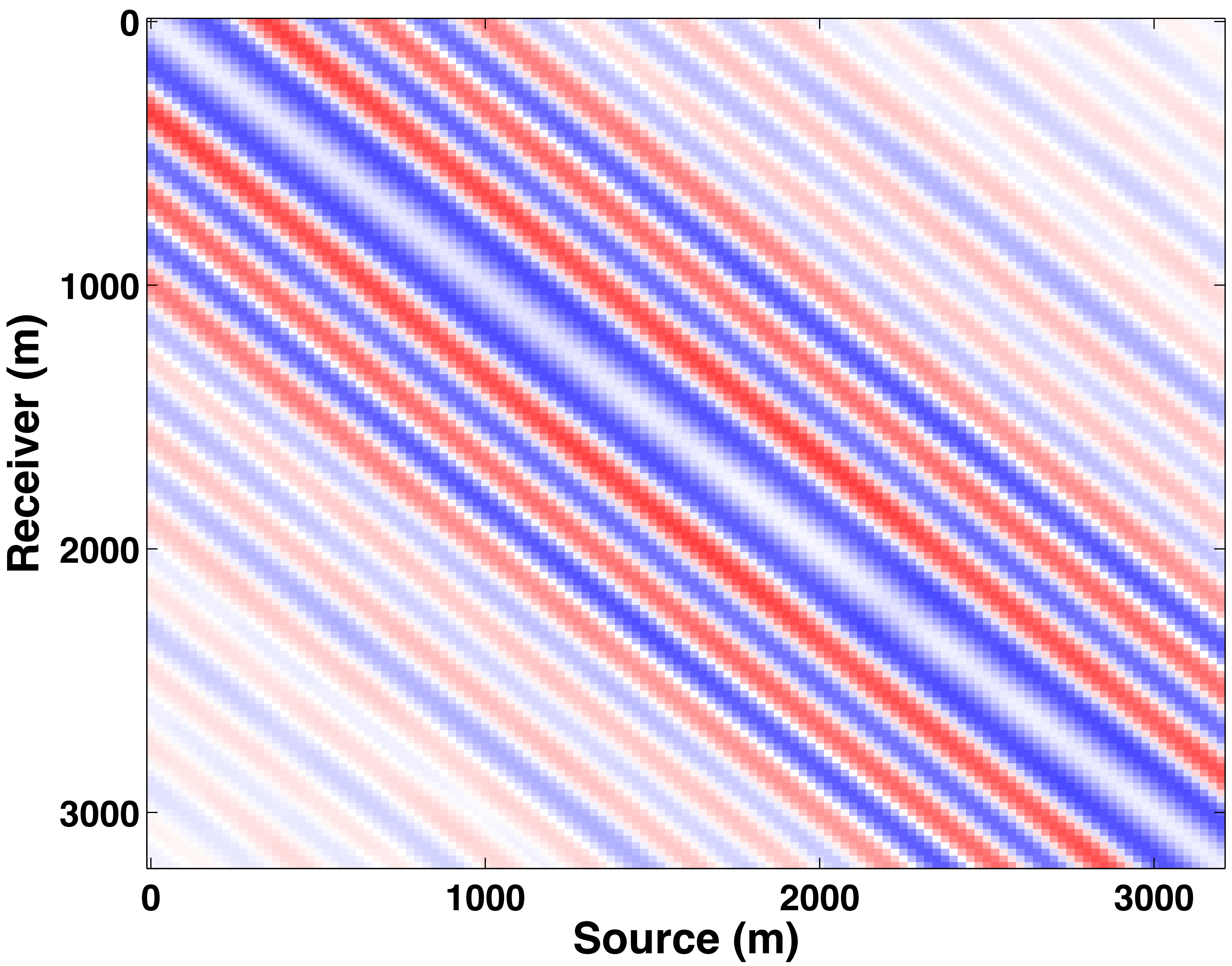
Decay of singular values



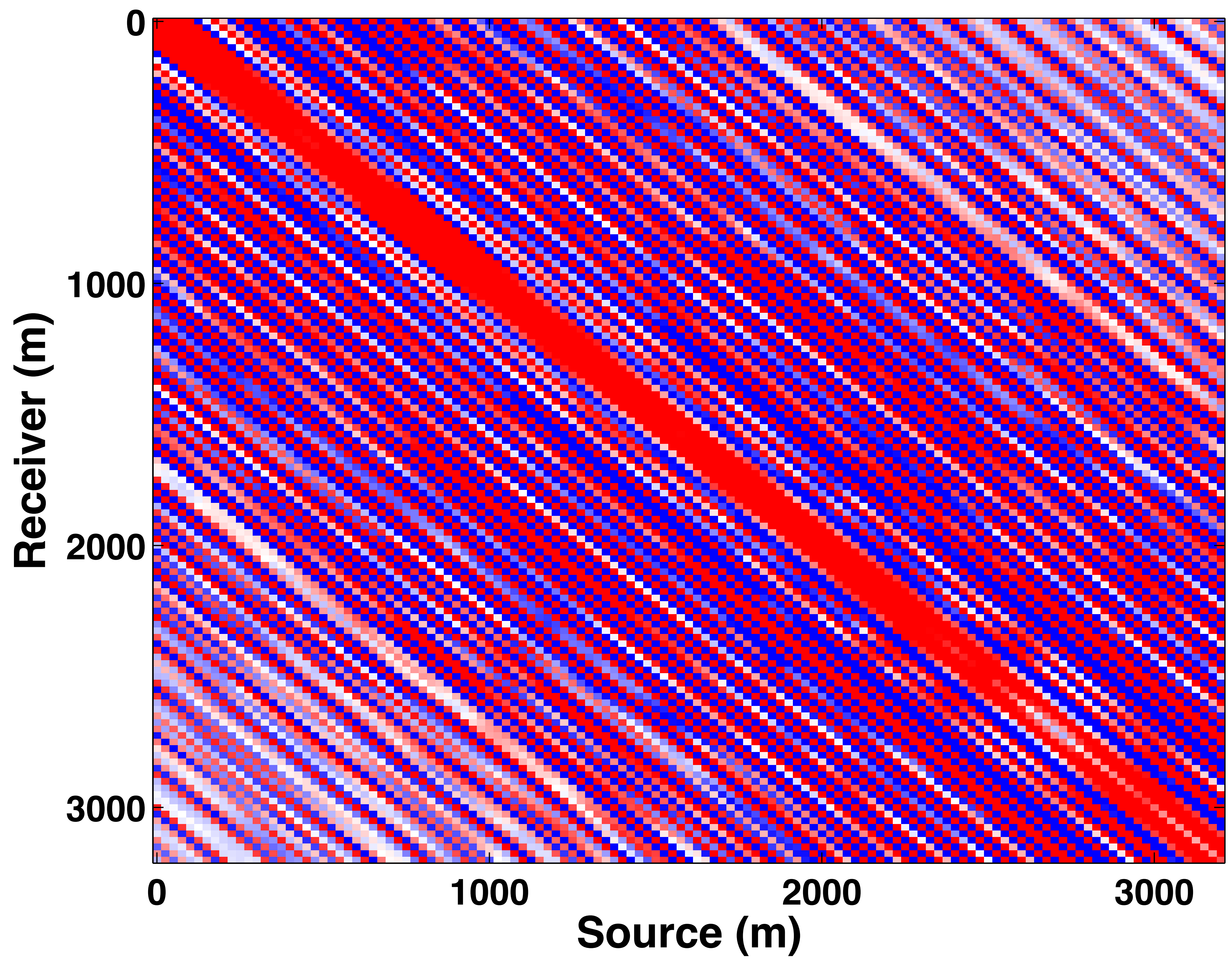


Are high frequencies low-rank?

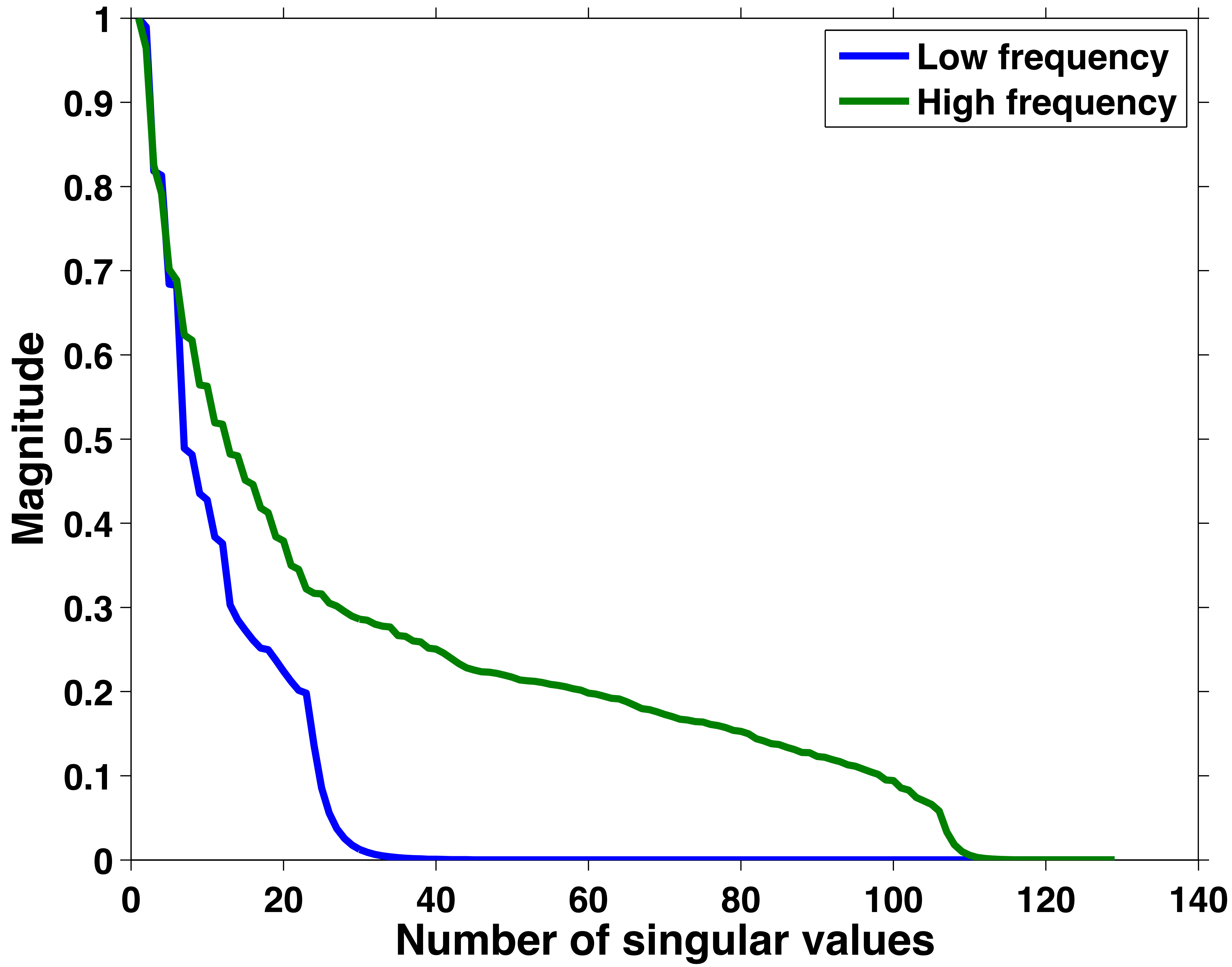
low frequency



high frequency



Decay of singular values



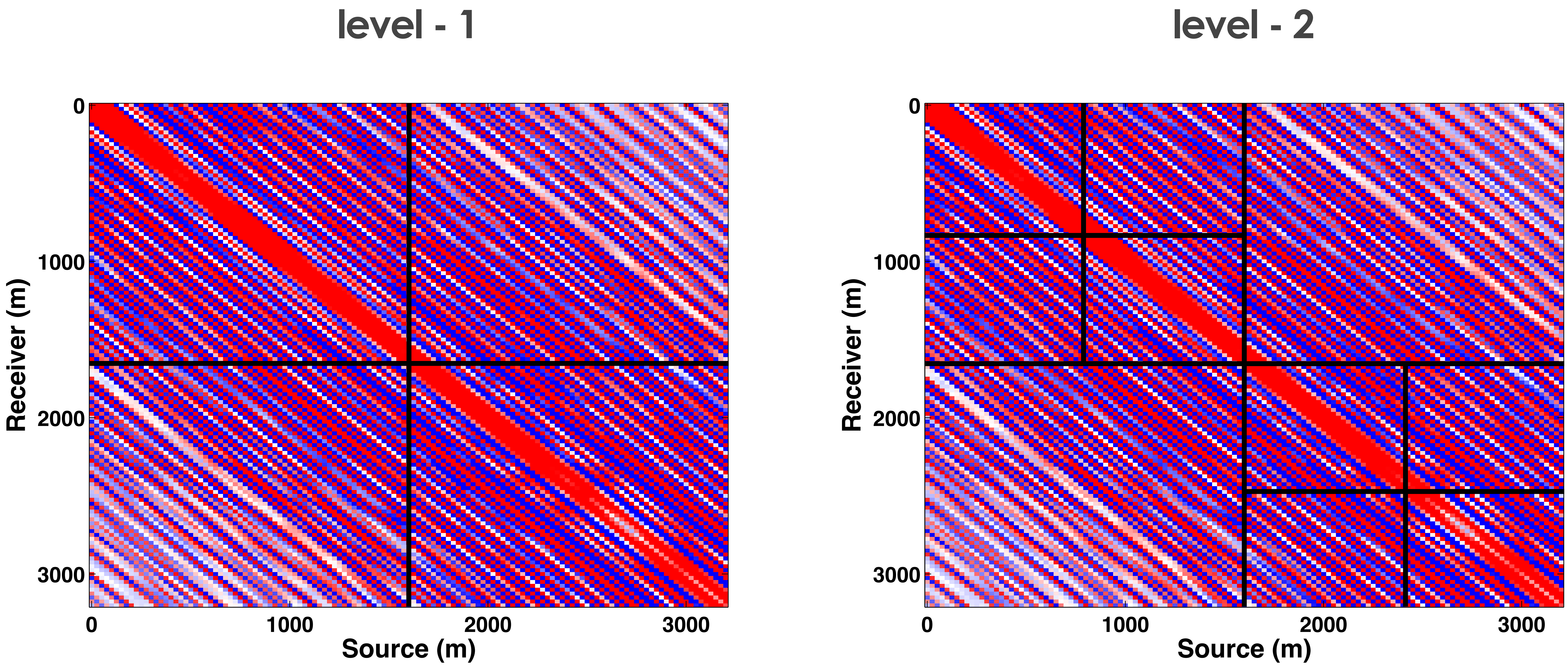
high frequencies do NOT have low-rank structure

Hierarchical semi-separable (HSS) representation

HSS representation

[Chandrasekaran, et. al., 2006]

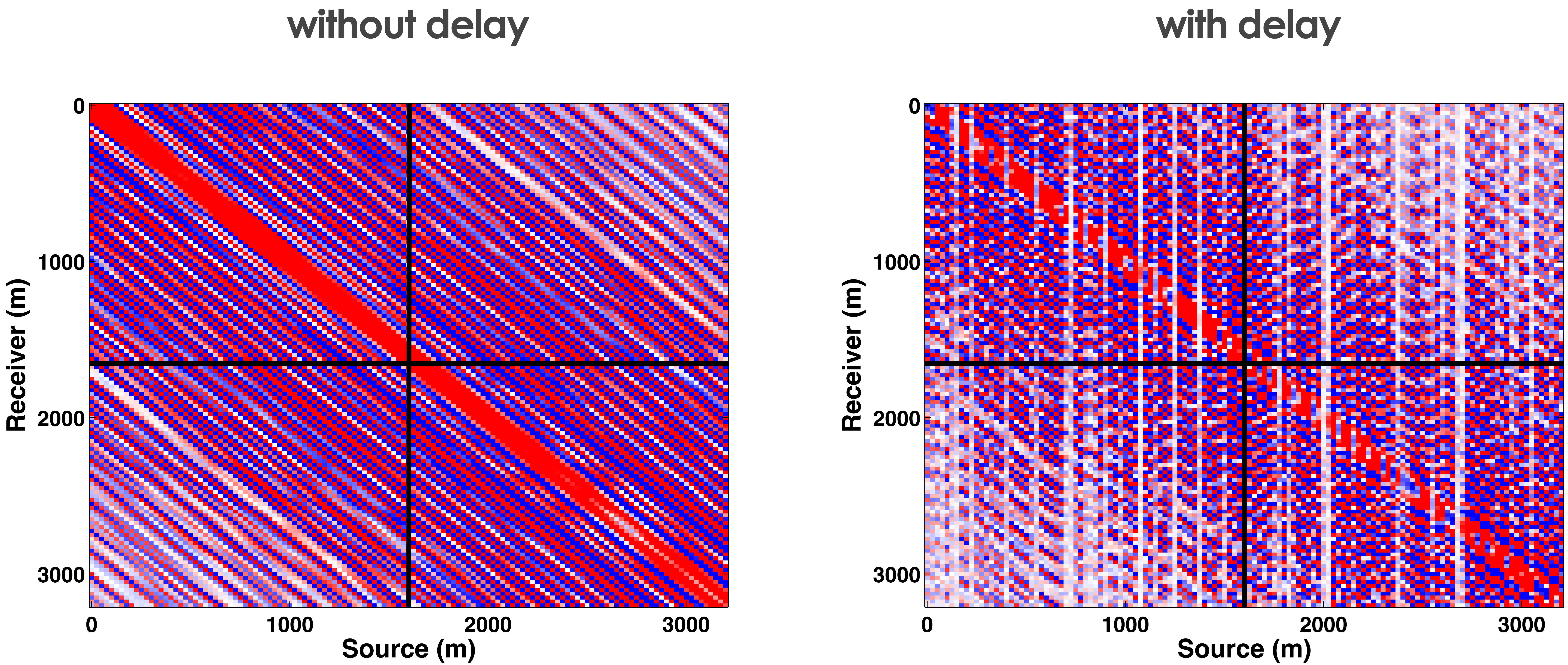
off-diagonals are low-rank



HSS representation

[Chandrasekaran, et. al., 2006]

level - 1 (applied)



Rank-minimization

Nuclear norm-minimization

Factorized formulation ("*SVD-free*")

Rank-minimization

$$\min_{\mathbf{X}} \quad \underbrace{\mathrm{rank}(\mathbf{X})} \quad \text{s.t.} \quad \|\mathcal{A}(\mathbf{X}) - \mathbf{b}\|_2 \leq \epsilon$$

number of singular values of $\mathbf{X}$

Rank-minimization

$$\min_{\mathbf{X}} \quad \underbrace{\operatorname{rank}(\mathbf{X})}_{} \quad \text{s.t.} \quad \|\mathcal{A}(\mathbf{X}) - \mathbf{b}\|_2 \leq \epsilon$$

number of singular values of $\mathbf{X}$

for blended acquisition:

$\mathbf{b}$: blended data

$$\mathcal{A} := \begin{bmatrix}\mathbf{M}\mathbf{S}^{\mathbf{H}} & \mathbf{M}\mathbf{T}\mathbf{S}^{\mathbf{H}}\end{bmatrix}$$

↑ time delay matrix

unblended data matrix

$$\mathbf{X} = \begin{bmatrix}\mathbf{X}_1 \\ \mathbf{X}_2\end{bmatrix}$$

$\mathbf{X}_1$ ⟵ source 1

$\mathbf{X}_2$ ⟵ source 2

Rank-minimization

expensive
(search over all possible values of rank)

$$\min_{\mathbf{X}} \quad \underbrace{\operatorname{rank}(\mathbf{X})} \quad \text{s.t.} \quad \|\mathcal{A}(\mathbf{X}) - \mathbf{b}\|_2 \leq \epsilon$$

number of singular values of $\mathbf{X}$

Rank-minimization

expensive
(search over all possible values of rank)

$$\min_{\mathbf{X}} \quad \underbrace{\mathrm{rank}(\mathbf{X})} \quad \text{s.t.} \quad \|\mathcal{A}(\mathbf{X}) - \mathbf{b}\|_2 \leq \epsilon$$

number of singular values of $\mathbf{X}$

Nuclear norm-minimization

convex relaxation of rank-minimization

[Recht, et. al., 2010]

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

sum of singular values of $\mathbf{X}$

Rank-minimization

expensive
(search over all possible values of rank)

$$\min_{\mathbf{X}} \quad \underbrace{\mathrm{rank}(\mathbf{X})} \quad \mathrm{s.t.} \quad \|\mathcal{A}(\mathbf{X}) - \mathbf{b}\|_2 \leq \epsilon$$

number of singular values of $\mathbf{X}$

Nuclear norm-minimization

convex relaxation of rank-minimization

[Recht, et. al., 2010]

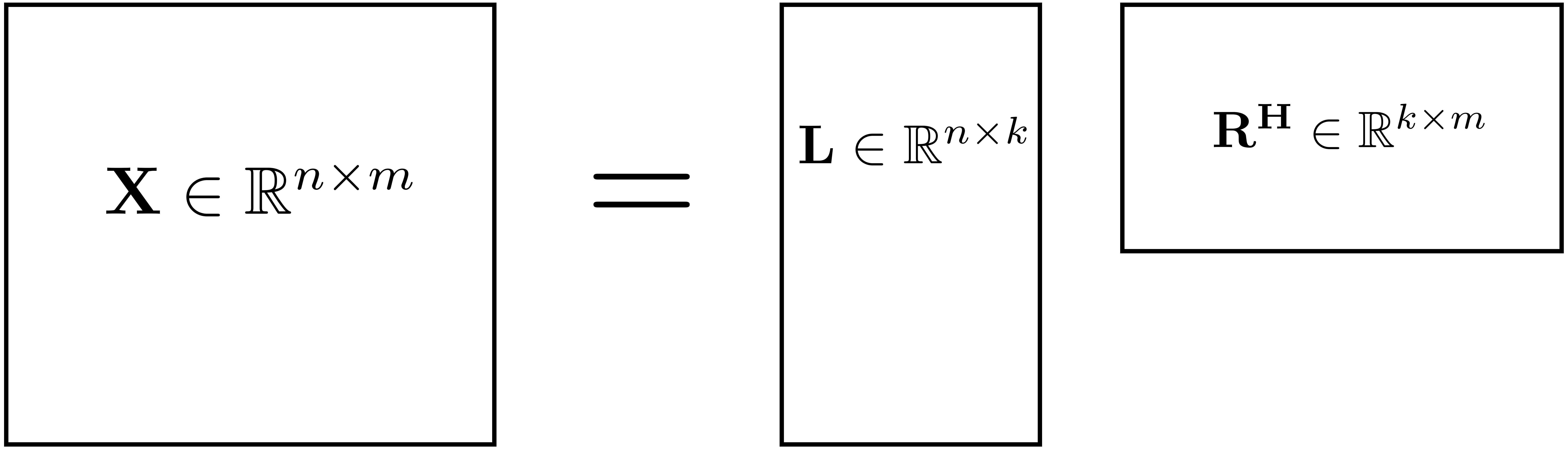
$$\min_{\mathbf{X}} \quad \underbrace{||\mathbf{X}||_*} \quad \mathrm{s.t.} \quad \|\mathcal{A}(\mathbf{X}) - \mathbf{b}\|_2 \leq \epsilon$$

sum of singular values of $\mathbf{X}$

however ...
requires repeated application of SVD

Factorized formulation ("*SVD-free*")

[Rennie and Srebro, 2005; Lee et. al., 2010; Recht and Re, 2011]



Upper-bound on nuclear norm:

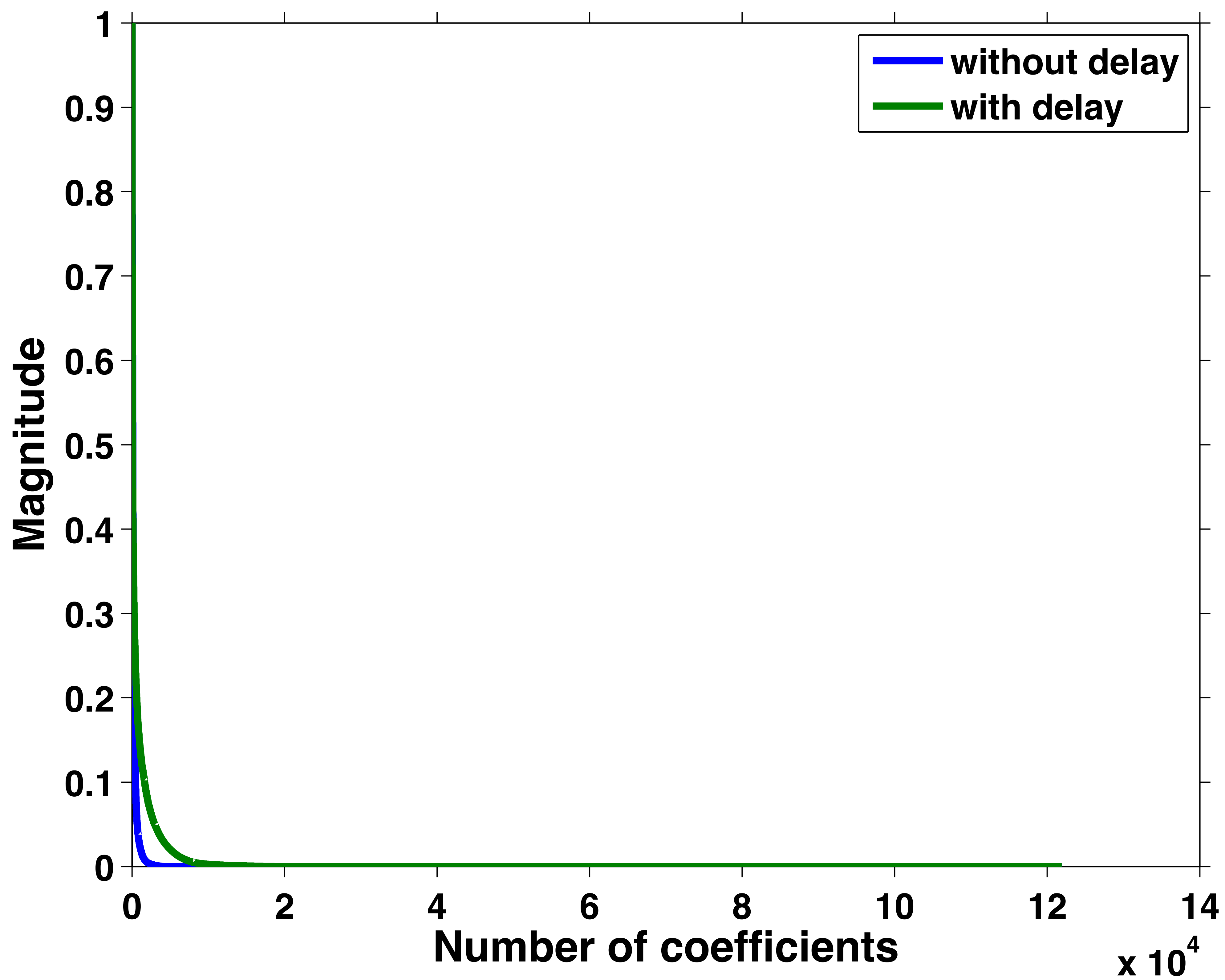
$$\|\mathbf{X}\|_* \leq \frac{1}{2}\left\|\begin{bmatrix}\mathbf{L}_1\\ \mathbf{R}_1\end{bmatrix}\right\|_F^2 + \frac{1}{2}\left\|\begin{bmatrix}\mathbf{L}_2\\ \mathbf{R}_2\end{bmatrix}\right\|_F^2 =: \Phi(\mathbf{L}_1, \mathbf{R}_1, \mathbf{L}_2, \mathbf{R}_2)$$

Sparsity-promotion

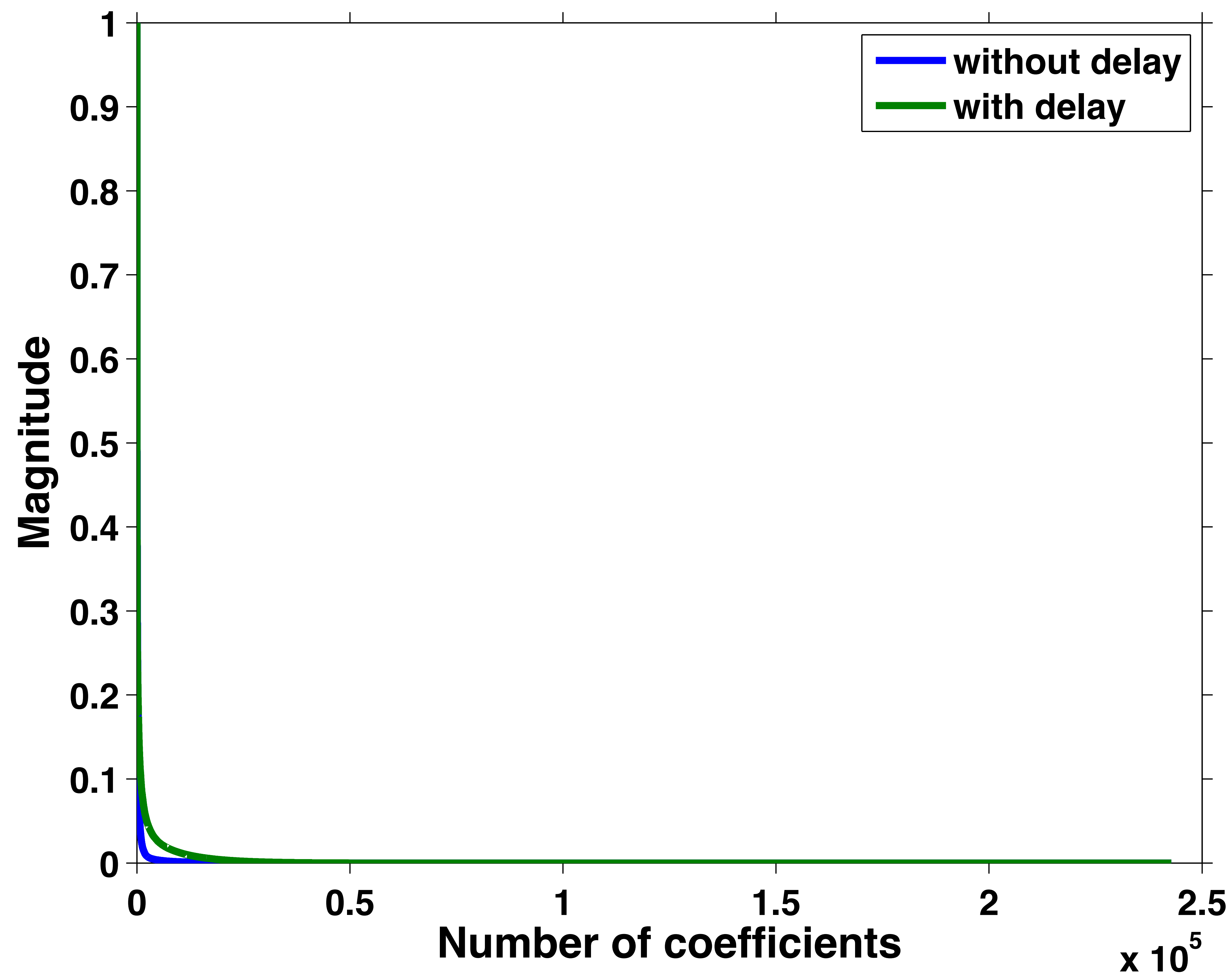
one norm-minimization

Decay of curvelet coefficients

source-receiver domain



midpoint-offset domain

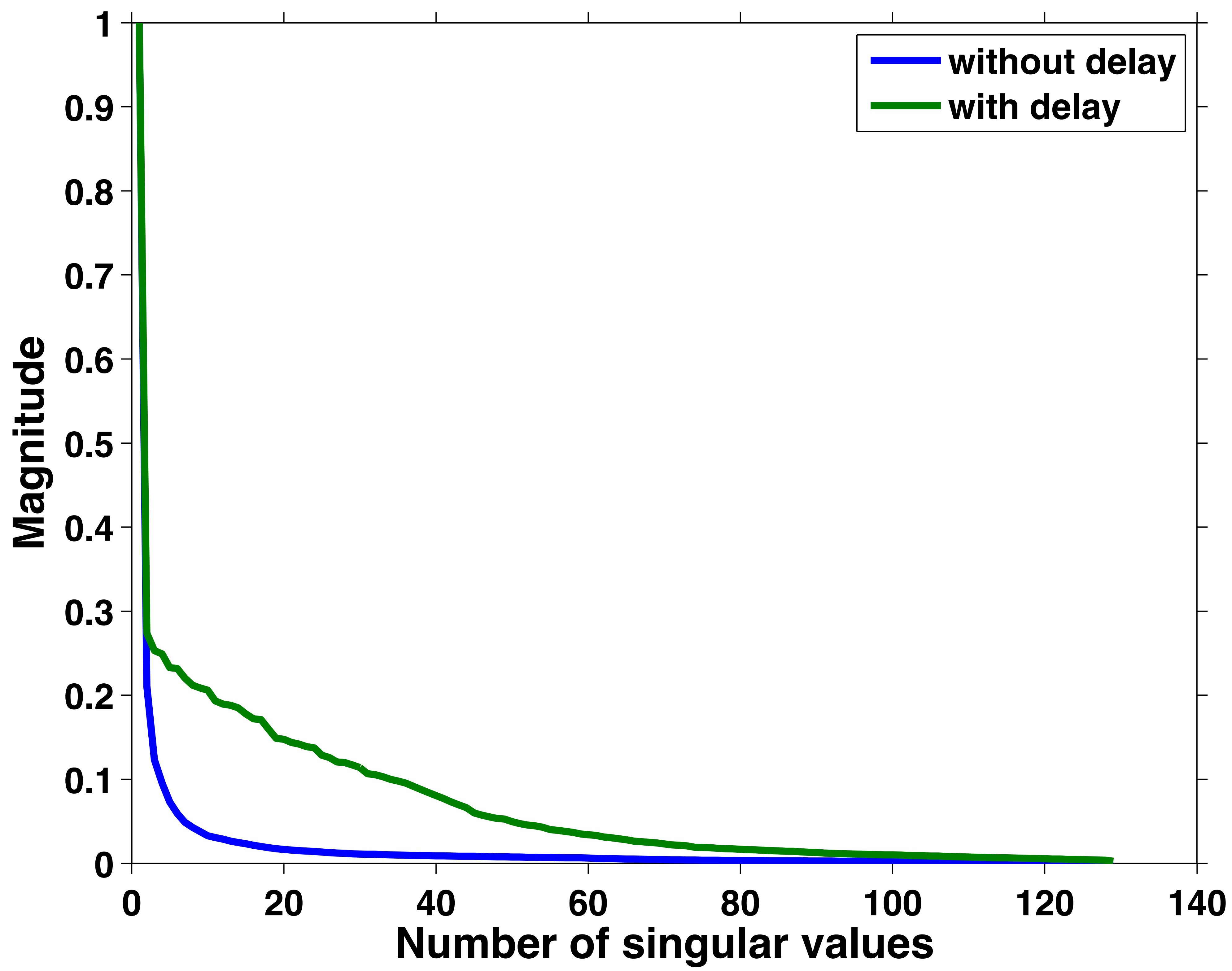


Source separation results

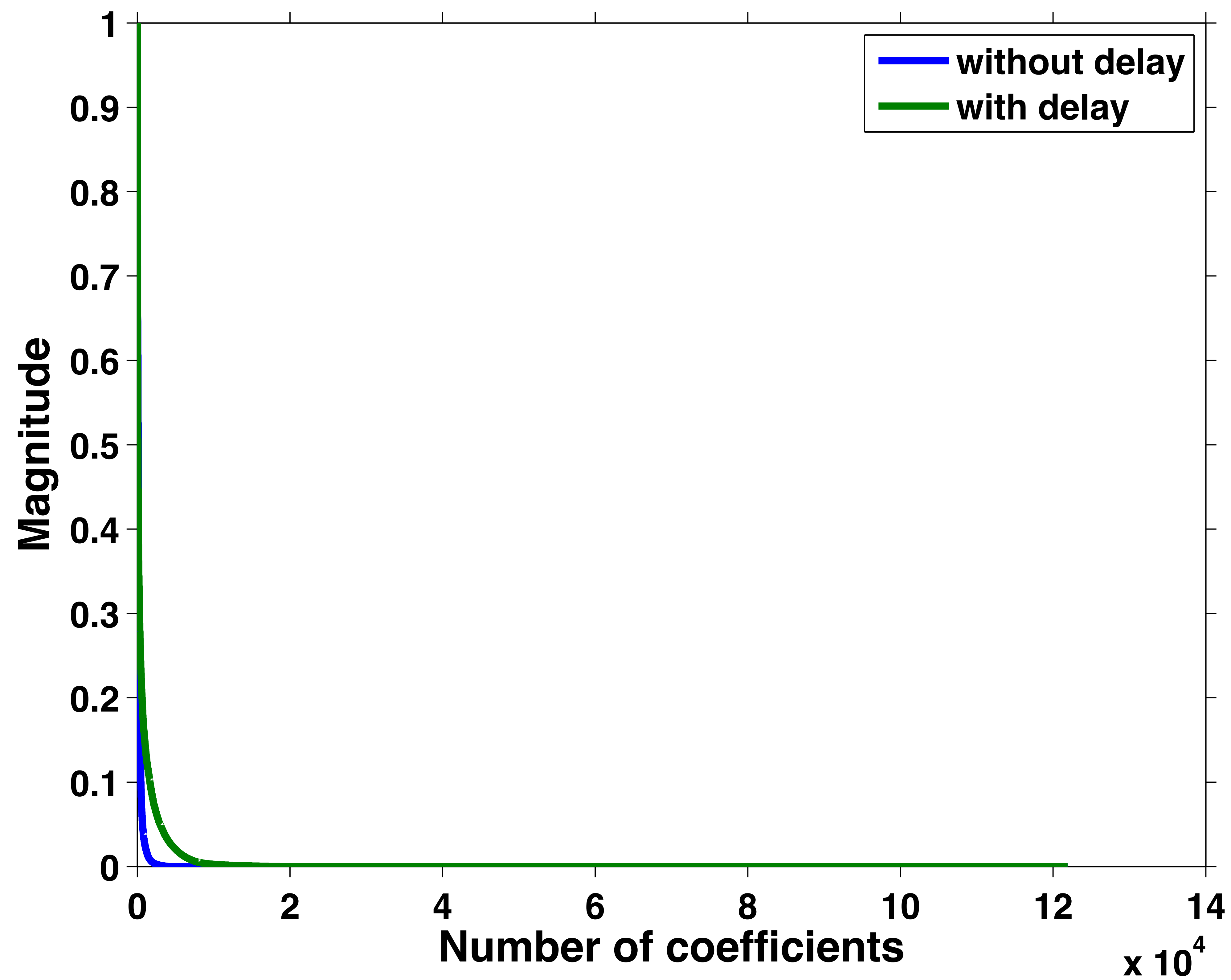
Rank-minimization vs. sparsity-promotion

Rank vs. sparsity

rank-minimization
(midpoint-offset domain)



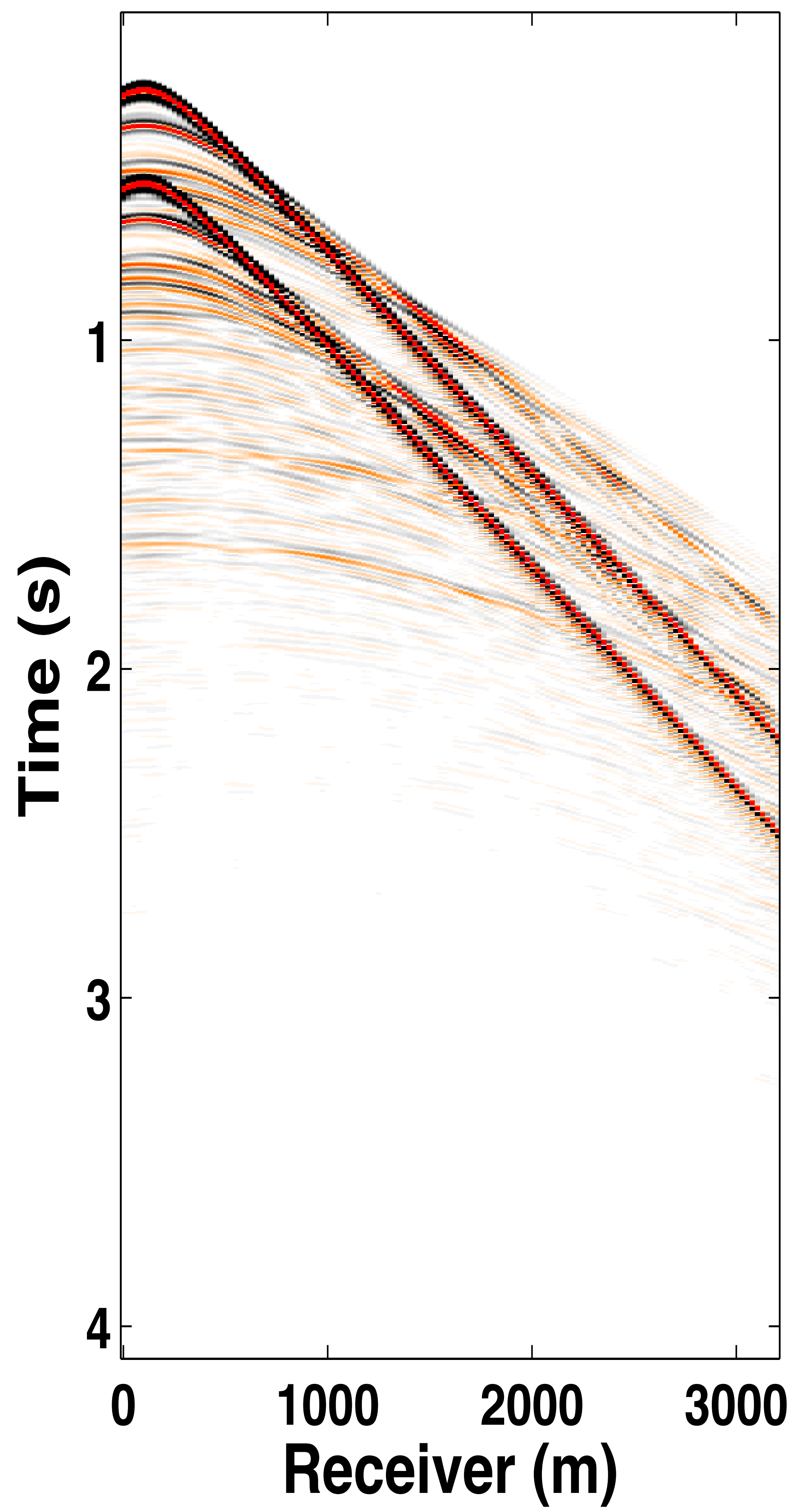
sparsity-promotion
(source-receiver domain)

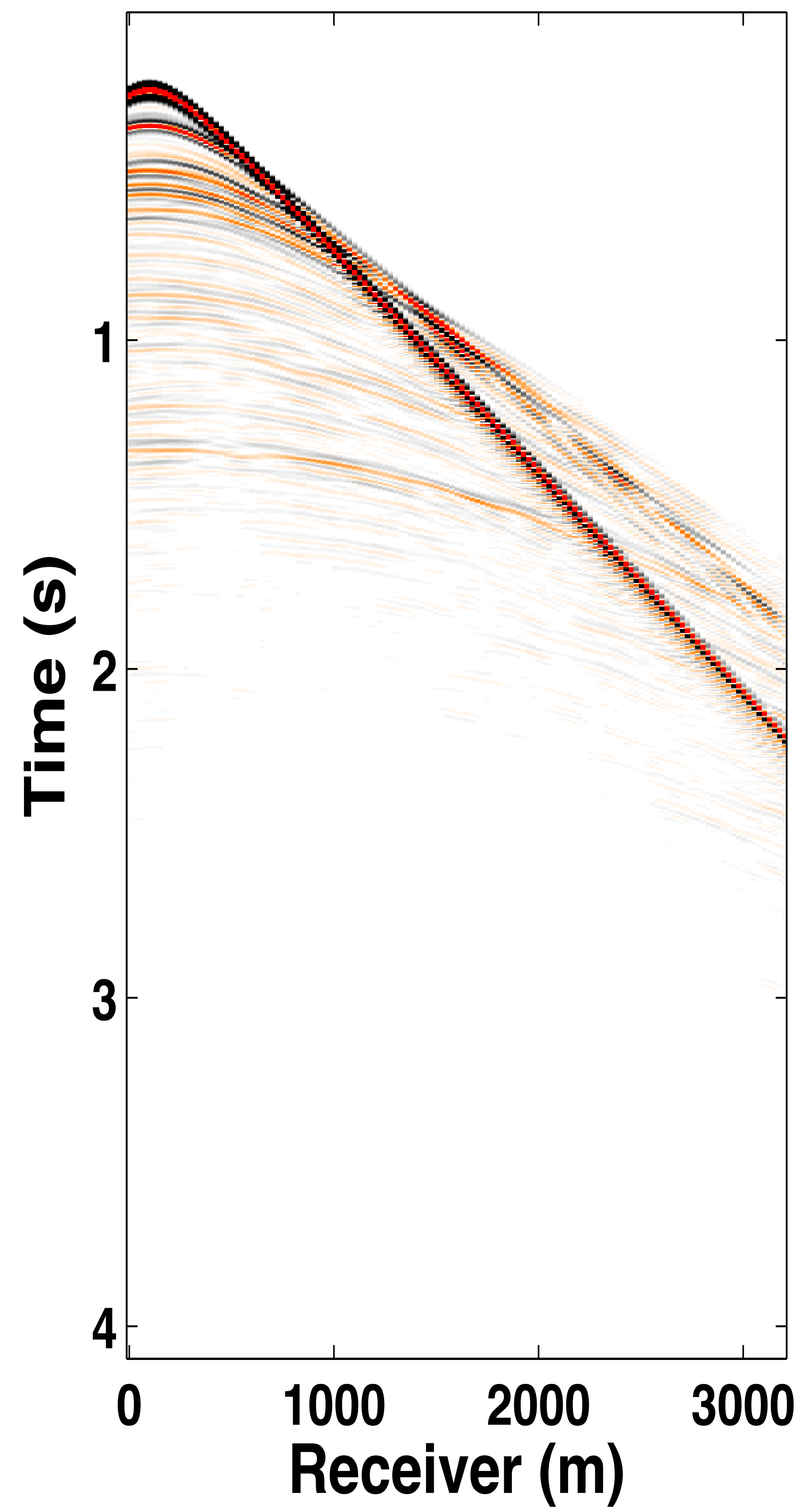


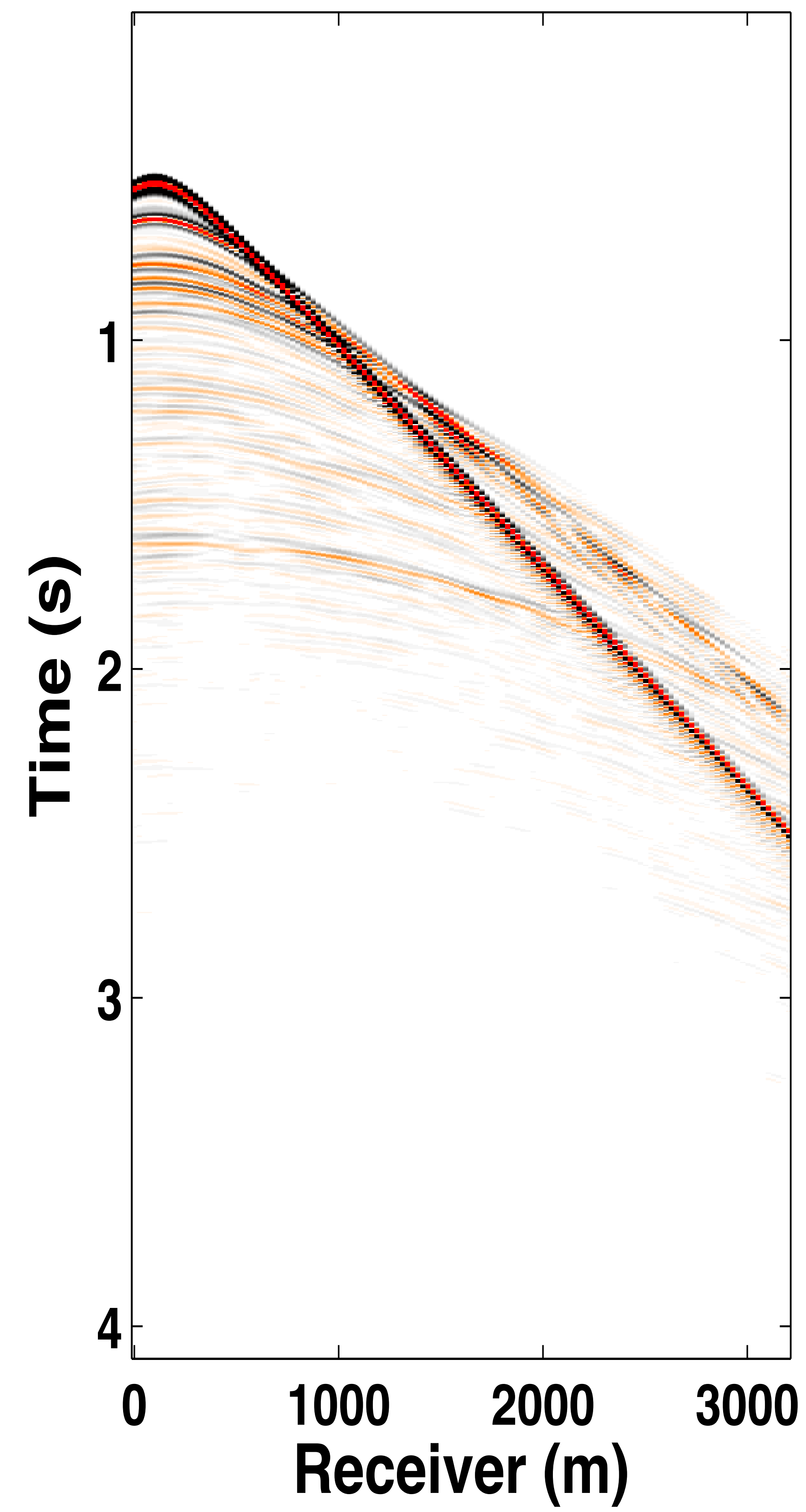
Blended data (w/ delay)

- random time delays applied to source 2

blended shot = **source 1** + **source 2 (time-delayed)**



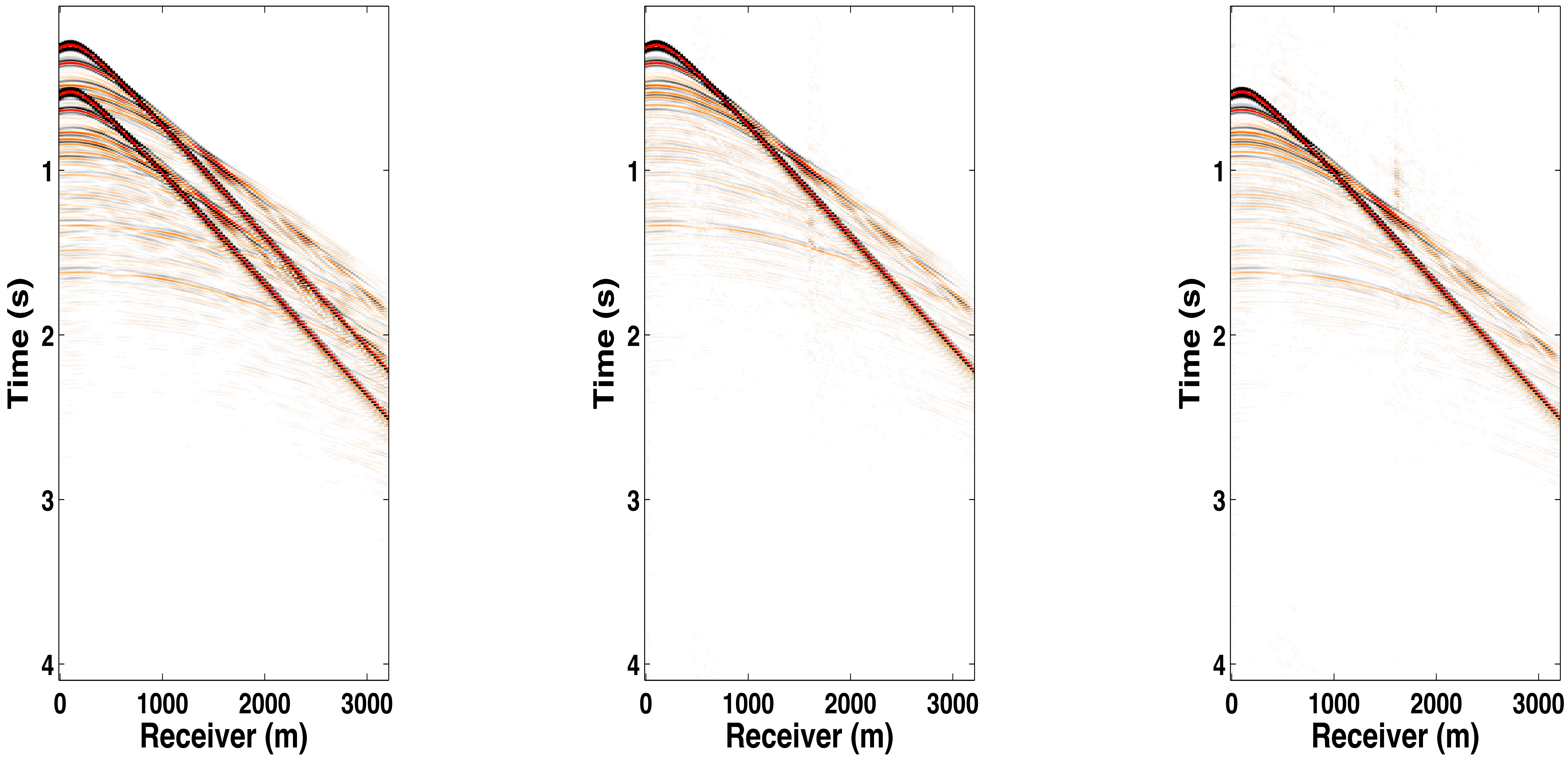




Source separation via *rank*-minimization

- computation time = **1.5** hours

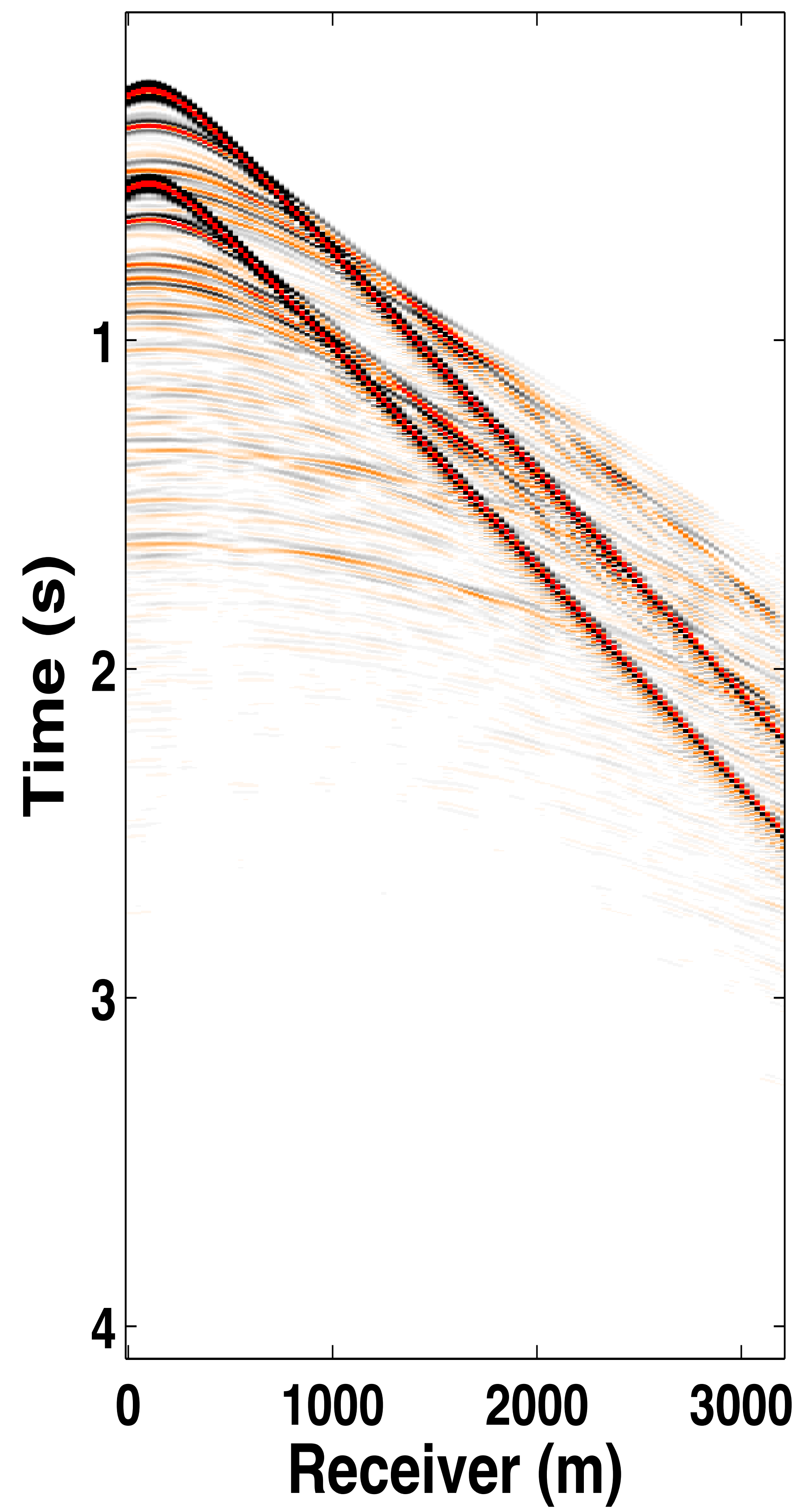
blended shot | **source 1** | **source 2 (time-delayed)**



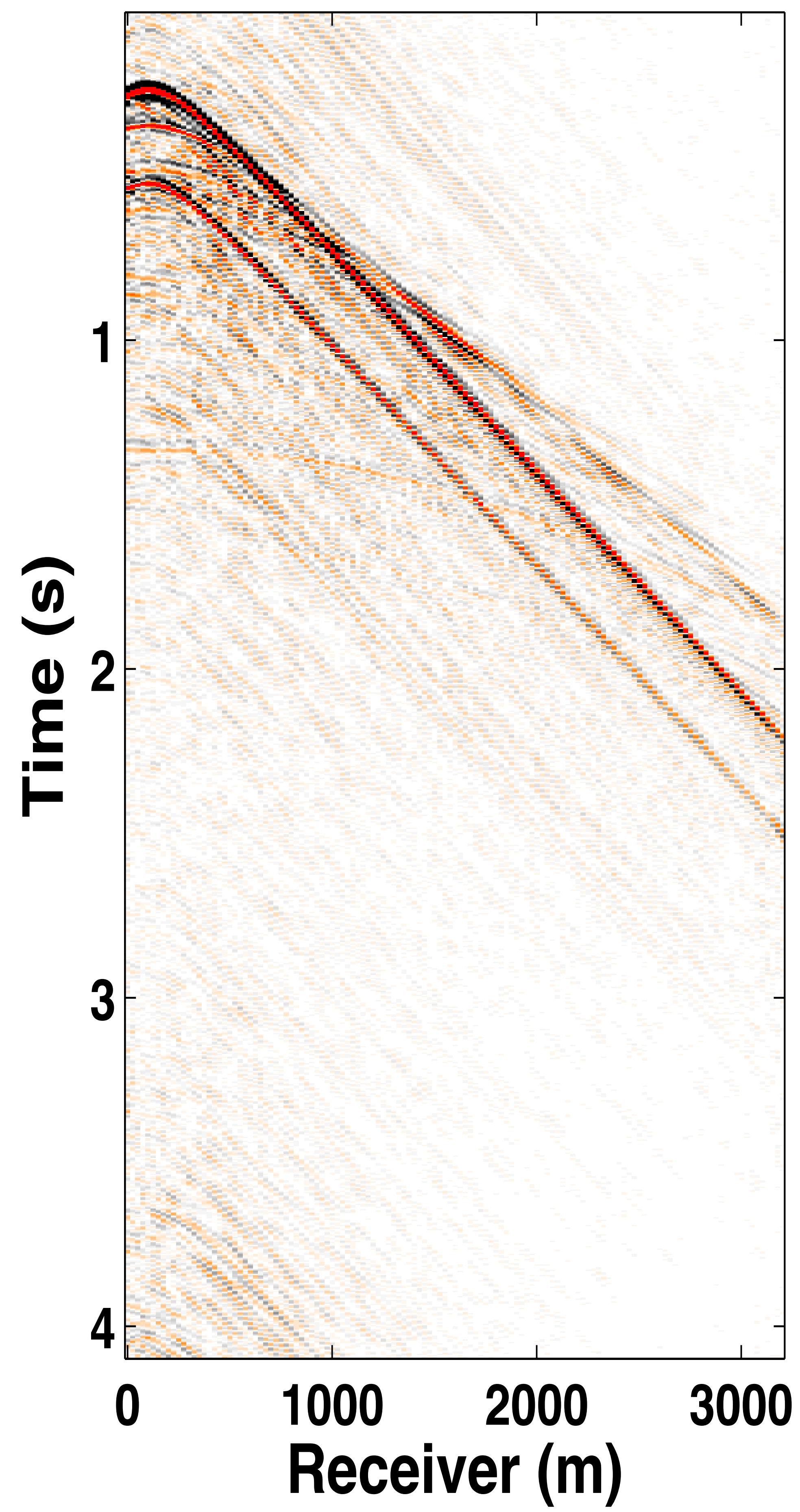
Source separation via *sparsity*-promotion

- computation time = 100 hours

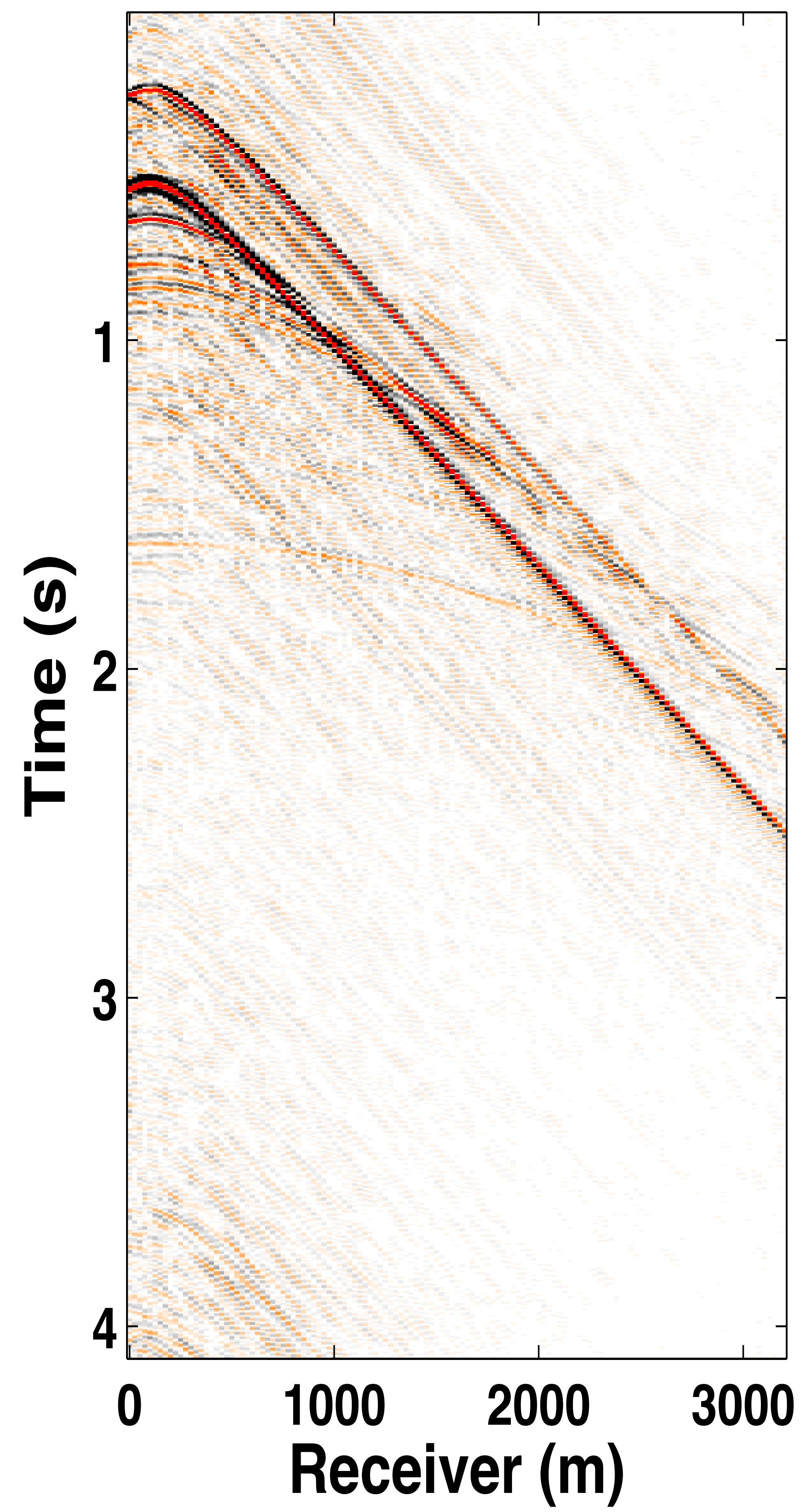
blended shot



source 1



source 2
(time-delayed)



Observations

Source separation for *low variability* acquisition scenarios can be treated as a *rank-minimization* problem

- e.g., towed-array (streamer) acquisition

Small variability in shot-times does *not* seem *desirable* for source separation via *sparsity-promotion*

Future work

More detailed comparisons of rank-minimization and sparsity-promoting techniques for source separation

Test with field data

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Acknowledgements

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