GeoConvention
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Compressive time-lapse seismic data processing using shared information

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Haneet Wason and Felix J. Herrmann, "Time-jittered ocean bottom seismic acquisition",
in *SEG Technical Program Expanded Abstracts*, 2013, vol. 32, p. 1-6.

Hassan Mansour, Haneet Wason, Tim T.Y. Lin, and Felix J. Herrmann, "Randomized marine acquisition with compressive sampling matrices",
Geophysical Prospecting, vol. 60, p. 648-662, 2012.

Time-lapse seismic

Current acquisition paradigm:

- *repeat* **expensive** dense acquisitions & *"independent"* processing
- compute *differences* between *baseline* & *monitor* survey(s)
- challenging to ensure *repetition*

New compressive sampling paradigm:

- cheap subsampled acquisition, e.g. via time-*jittered* marine *undersampling*
- exploits insights from distributed compressive sensing
- may offer possibility to *relax* insistence on *repeatability*

Compressive sensing

Sampling

$$\mathbf{A}_1\mathbf{x}_1 = \mathbf{b}_1$$

subsampled
baseline data

$$\mathbf{A}_2\mathbf{x}_2 = \mathbf{b}_2$$

subsampled
monitor data

Sparsity-promoting recovery

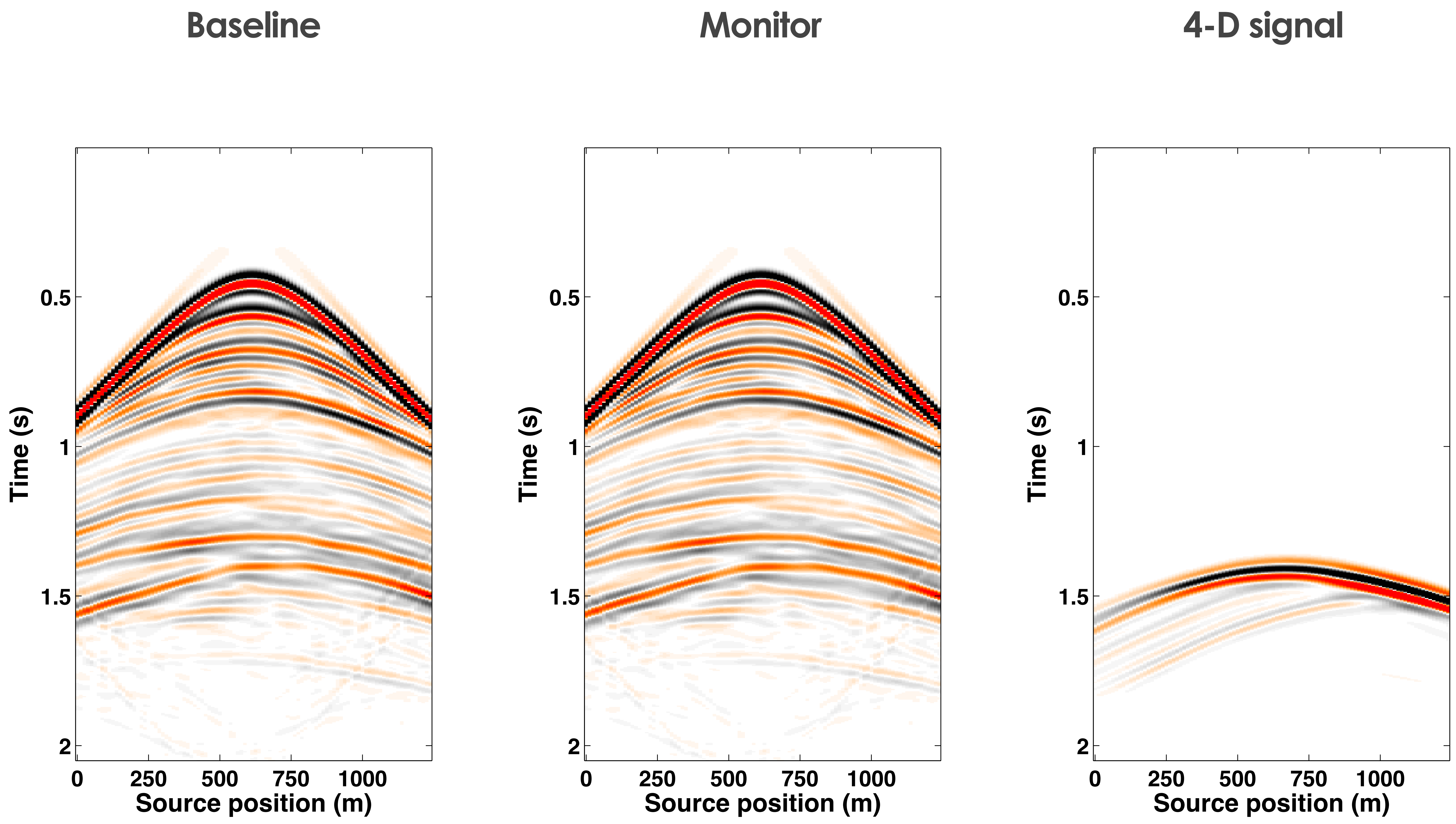
$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \mathbf{A}\mathbf{x} = \mathbf{b}$$

$\mathbf{A}$ sampling matrix

Probing time-lapse data ....

Simulated original data

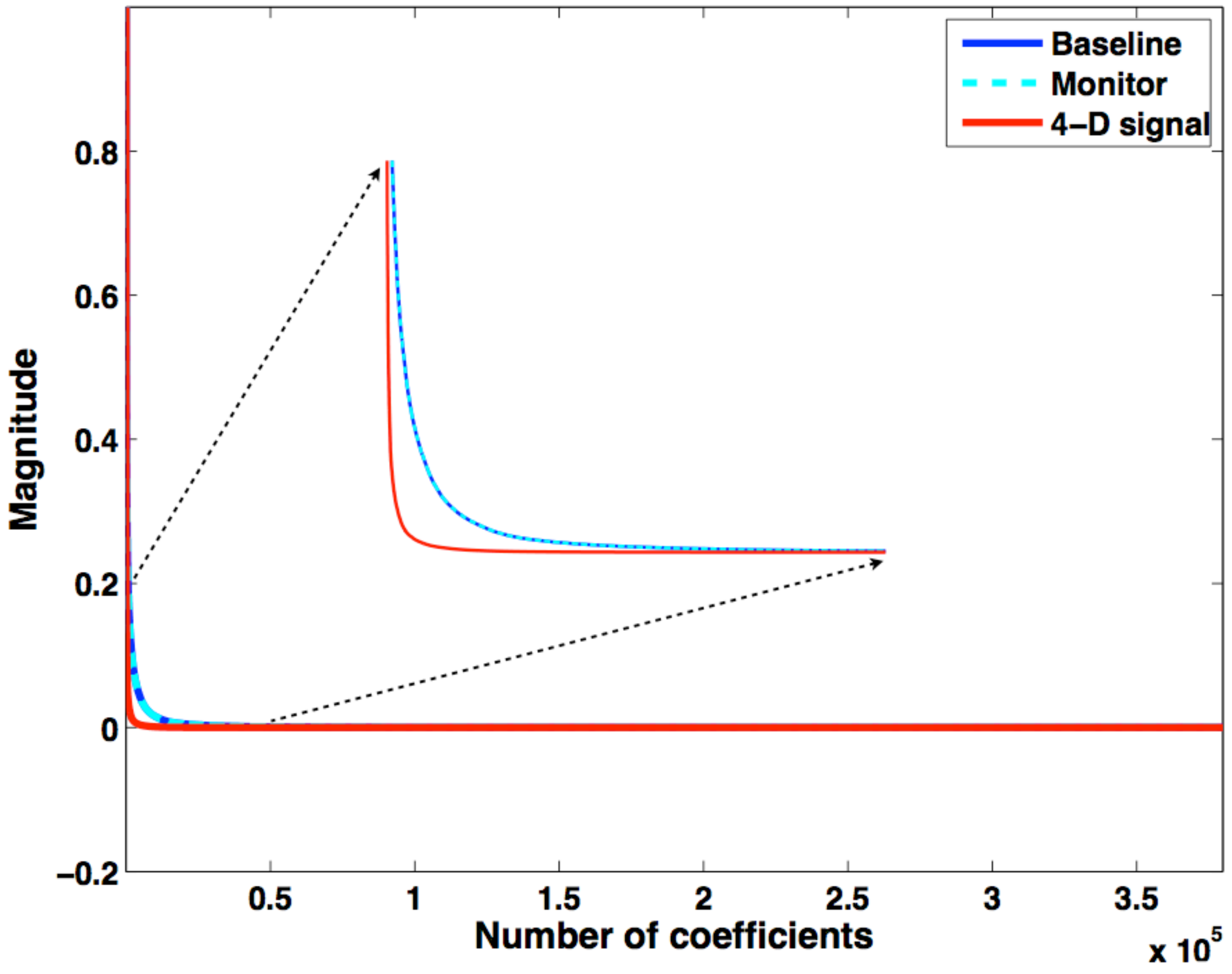
– time-domain finite differences

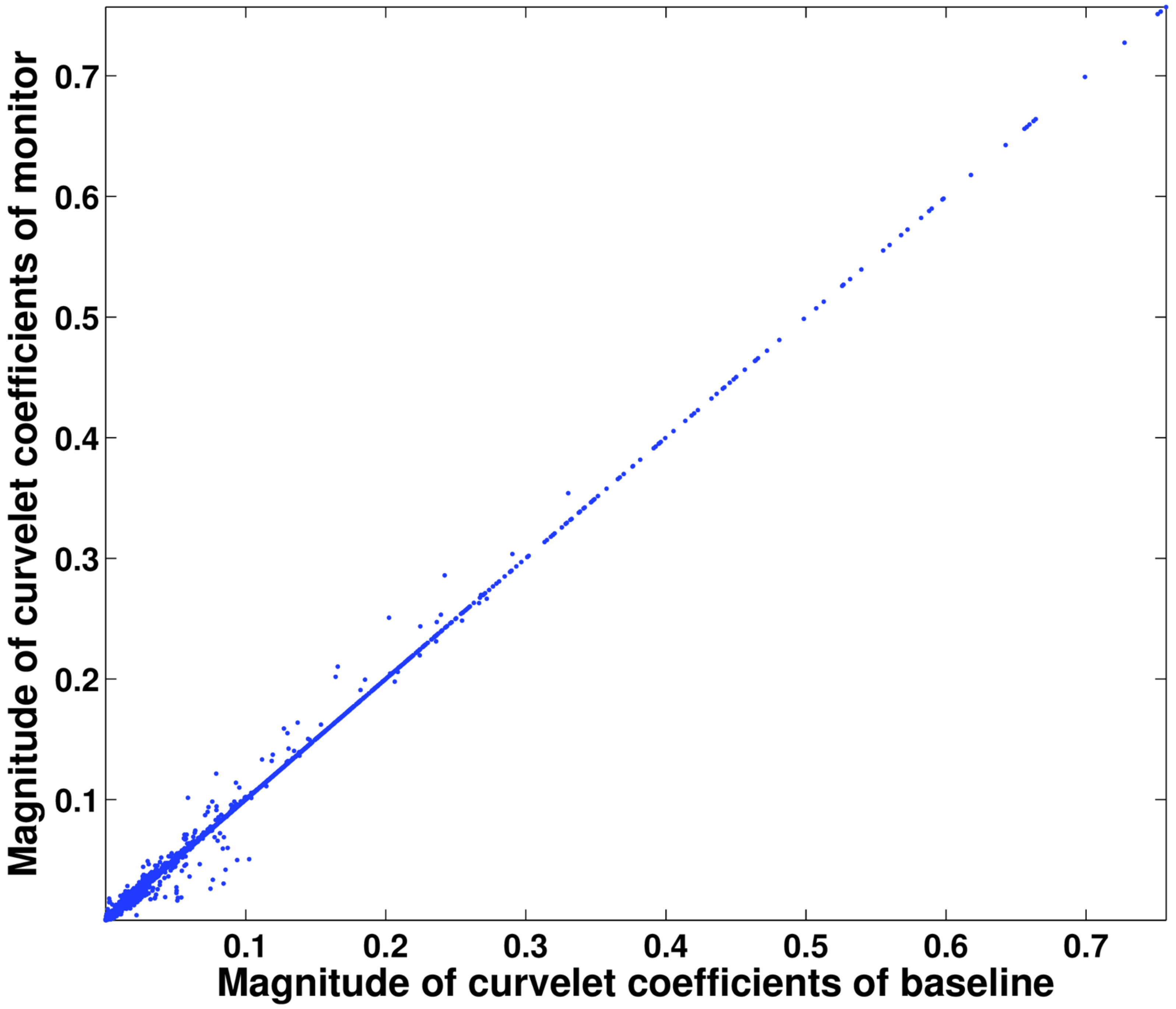


time samples: **512**
receivers: **100**
sources: **100**

sampling
time: **4.0 ms**
receiver: **12.5 m**
source: **12.5 m**

Structure - curvelet representation





Observations

- Compressible
  - few coefficients needed for reconstruction
- Correlations in different vintages
  -significant overlap along the diagonal
- Time-lapse signal
  -more compressible

Can we exploit the structure in the time-lapse data simultaneously ?

Dror Baron , Marco F. Duarte , Shriram Sarvotham , Michael B. Wakin , Richard G. Baraniuk. An Information-Theoretic Approach to Distributed Compressed Sensing (2005)

Distributed compressive sensing

– *joint* recovery model (JRM)

vintages

$$\mathbf{x}_1 = \mathbf{z}_0 + \mathbf{z}_1$$

$$\mathbf{x}_2 = \mathbf{z}_0 + \mathbf{z}_2$$

differences

***common* component**

$$\overbrace{\begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_1 & \mathbf{0} \\ \mathbf{A}_2 & \mathbf{0} & \mathbf{A}_2 \end{bmatrix}}^{\mathbf{A}} \overbrace{\begin{bmatrix} \mathbf{z}_0 \\ \mathbf{z}_1 \\ \mathbf{z}_2 \end{bmatrix}}^{\mathbf{z}} = \overbrace{\begin{bmatrix} \mathbf{b}_1 \\ \mathbf{b}_2 \end{bmatrix}}^{\mathbf{b}}$$

baseline

monitor

- **Key idea:**
  - use the fact that *different* vintages *share* common information
  - invert for *common* components & *differences* w.r.t. the *common* components with *sparse* recovery

Interpretation of the model

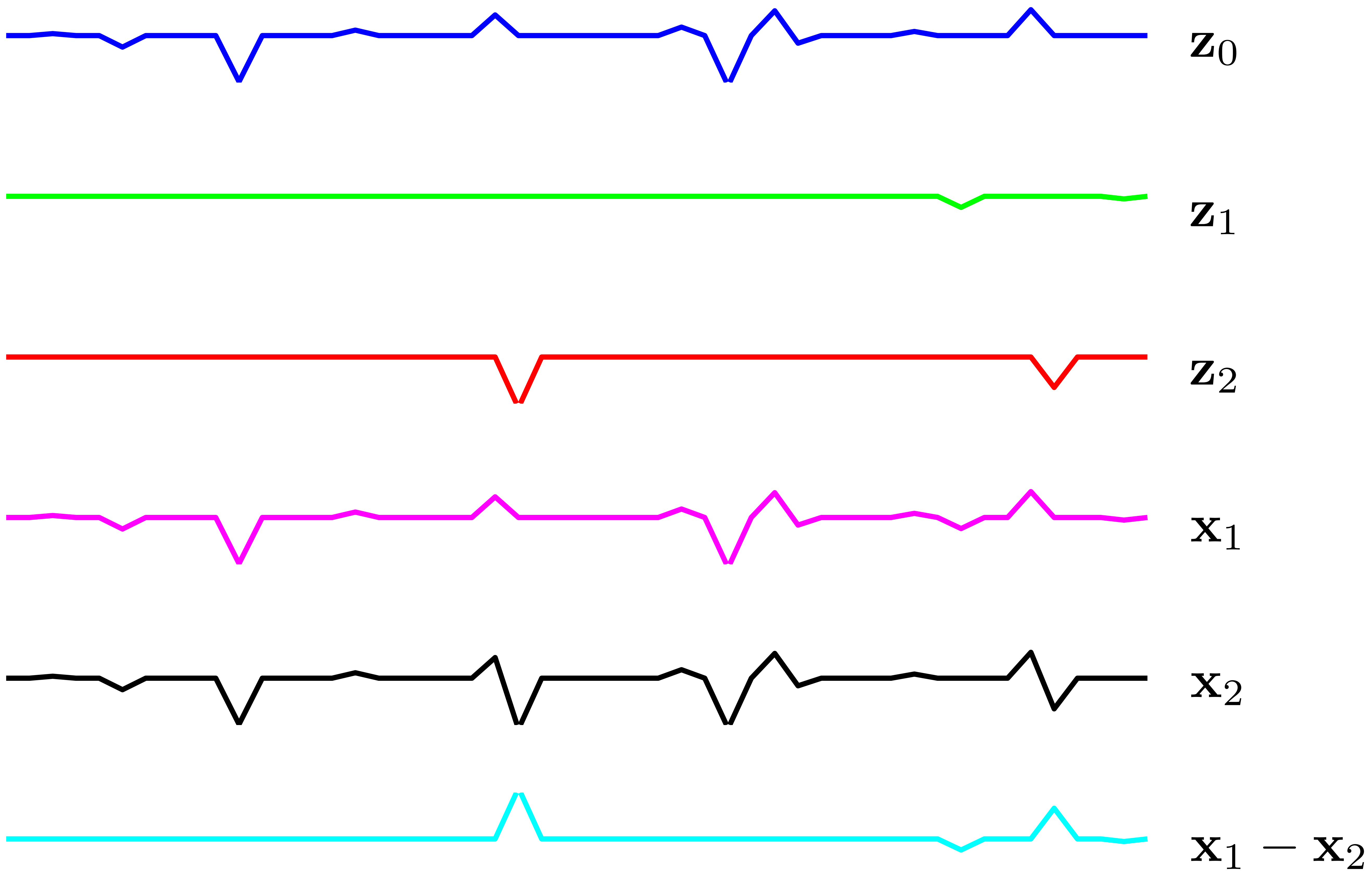
– w/ & w/o repetition

- **In an *ideal* world** $(\mathbf{A}_1 = \mathbf{A}_2)$
  - JRM *simplifies* to recovering the *difference* from $(\mathbf{b}_2 - \mathbf{b}_1) = \mathbf{A}_1(\mathbf{x}_2 - \mathbf{x}_1)$
  - expect *good* recovery when *difference* is *sparse*
  - ***but*** relies on “*exact*” repeatability…

- **In the *real* world** $(\mathbf{A}_1 \neq \mathbf{A}_2)$
  - no absolute *control* on *surveys*
  - *calibration* errors
  - noise…

Stylized examples

Sparse baseline, monitor and time-lapse signals



common component

“difference”

“difference”

baseline

monitor

time-lapse

Signal length N = 50

Stylized experiments

Conduct *many* CS experiments to compare

- *joint* vs *parallel* recovery of signals and the difference
- recovery with *completely* independent $\mathbf{A}_1,\ \mathbf{A}_2$
- *random* acquisition with different numbers of samples

Stylized experiments

Conduct *many* CS experiments to compare

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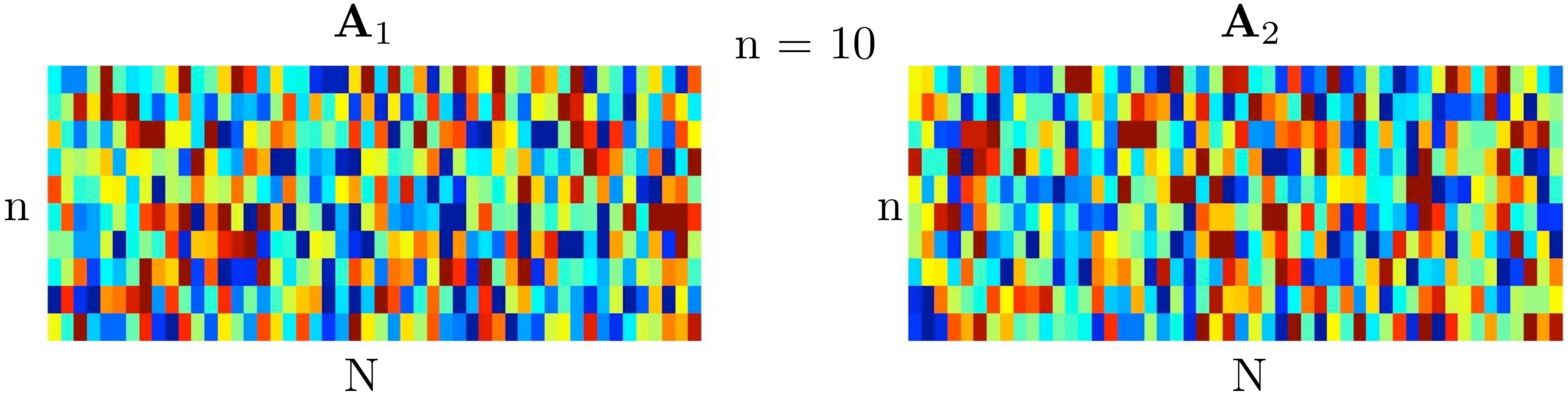
- recovery with *completely* independent $\mathbf{A}_1, \ \mathbf{A}_2$
- *random* acquisition with different numbers of samples



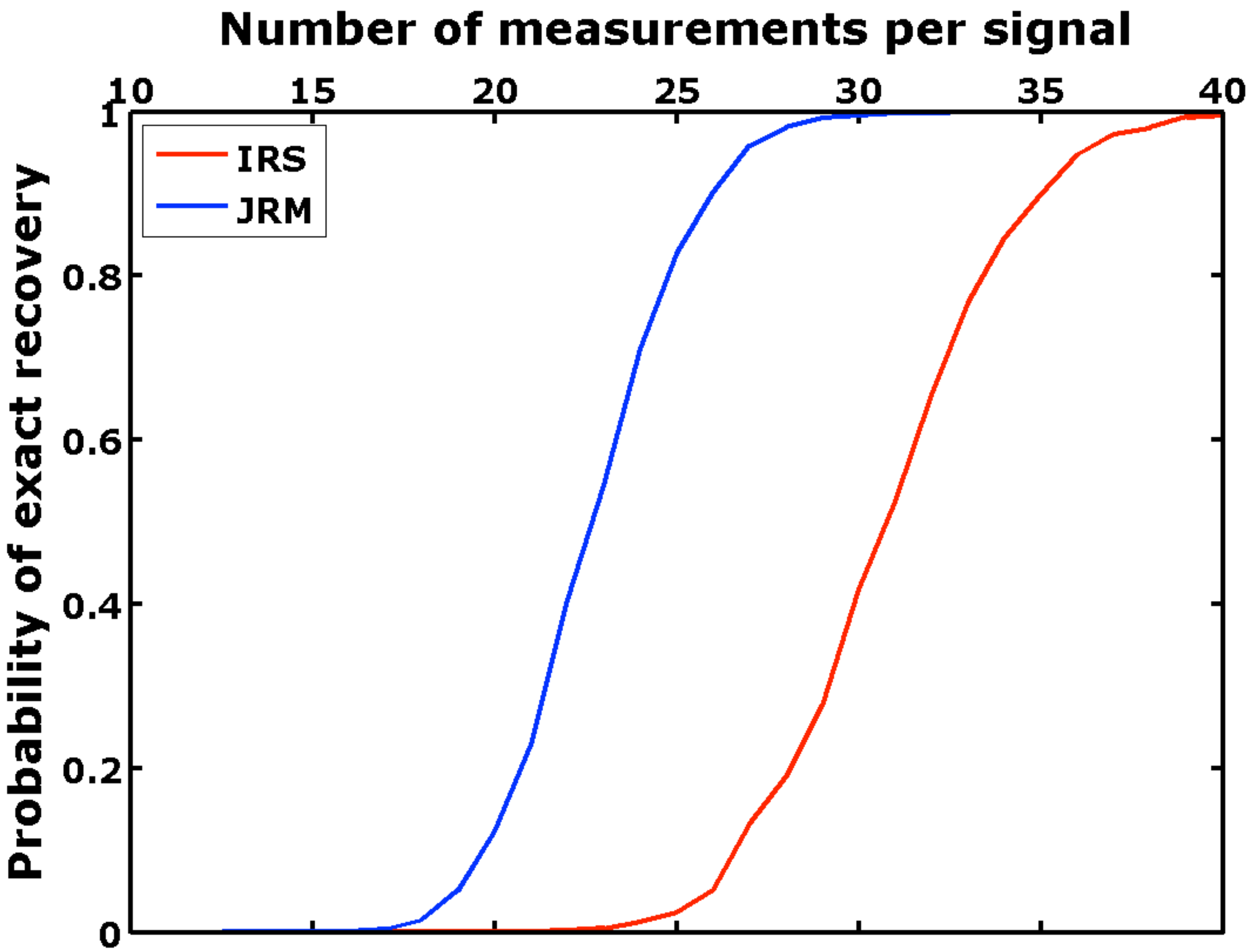
$\mathbf{b}_1 = \mathbf{A}_1\mathbf{x}_1$

$\mathbf{b}_2 = \mathbf{A}_2\mathbf{x}_2$

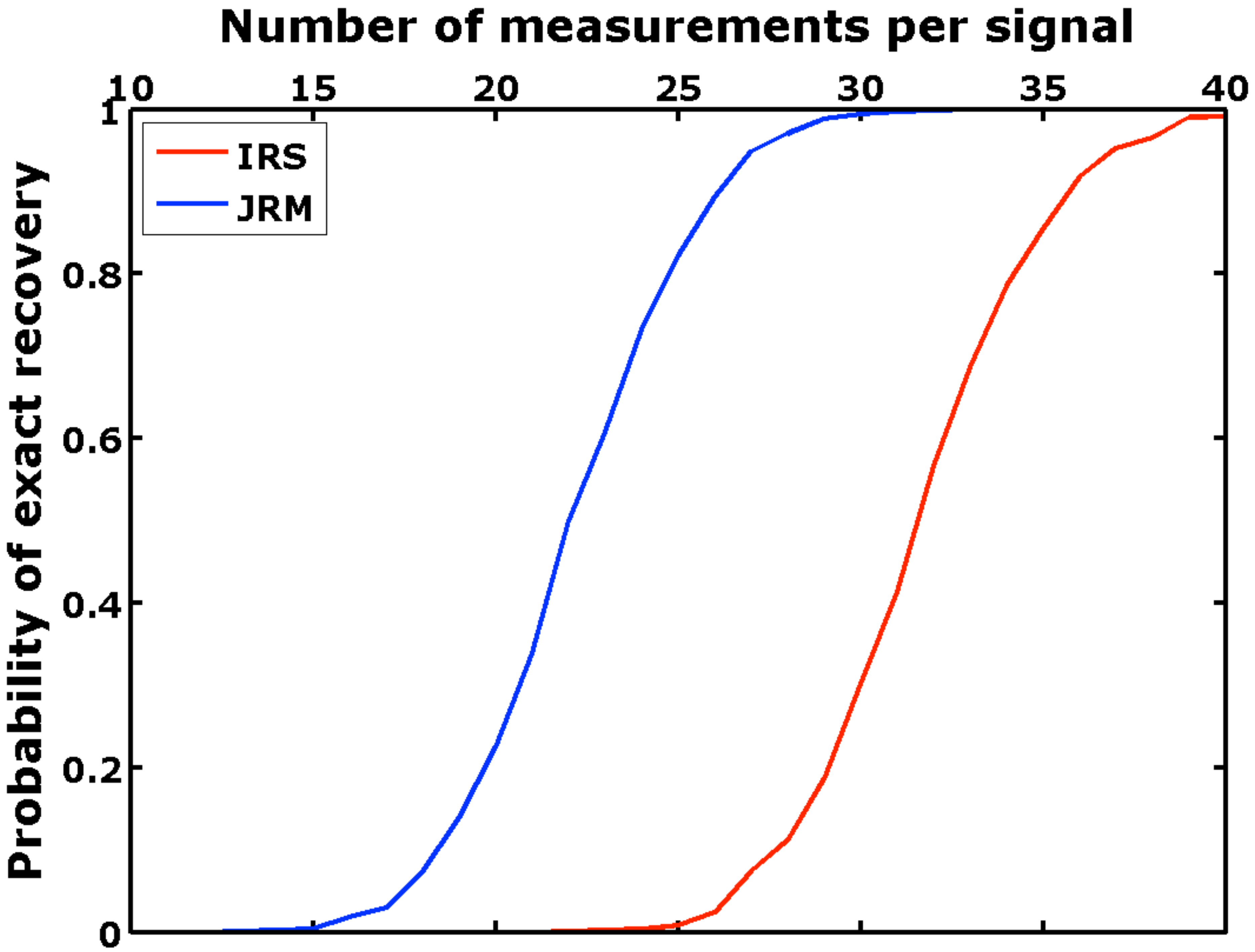
Run 2000 different experiments

Compute Probability of recovery

Results: *independent* versus *joint* recovery



Recovery of vintages



Recovery of difference

Observations

- Joint recovery (processing) is better than independent processing
- Improved recovery of vintages and difference
- Requires fewer samples (subsampled data)

Application to imaging

- credit to Ning Tu

Ning Tu and Felix J. Herrmann, "**Fast imaging with surface related multiples by sparse inversion**", *Geophysical Journal International*, vol. 201, p. 304-317, 2014.

Felix J. Herrmann and Xiang Li, "**Efficient least-squares imaging with sparsity promotion and compressive sensing**", *Geophysical Prospecting*, vol. 60, p. 696-712, 2012.

Migration

Problem formulation

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \|\mathbf{A}\mathbf{x} - \mathbf{b}\|_2 \leq \sigma$$

where

$$\mathbf{A} = \overbrace{\nabla \mathrm{F}[\mathbf{m}_0, q]}^{\textbf{Linearized Demigration operator}}\mathbf{C}^H$$

$$\mathbf{b} = \delta\mathbf{d}$$

$$\delta\tilde{\mathbf{m}} = \mathbf{C}^H\tilde{\mathbf{x}}$$

Migration

Dimensionality reduction

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \|\underline{\mathbf{A}}\mathbf{x} - \underline{\mathbf{b}}\|_2 \leq \sigma_k$$

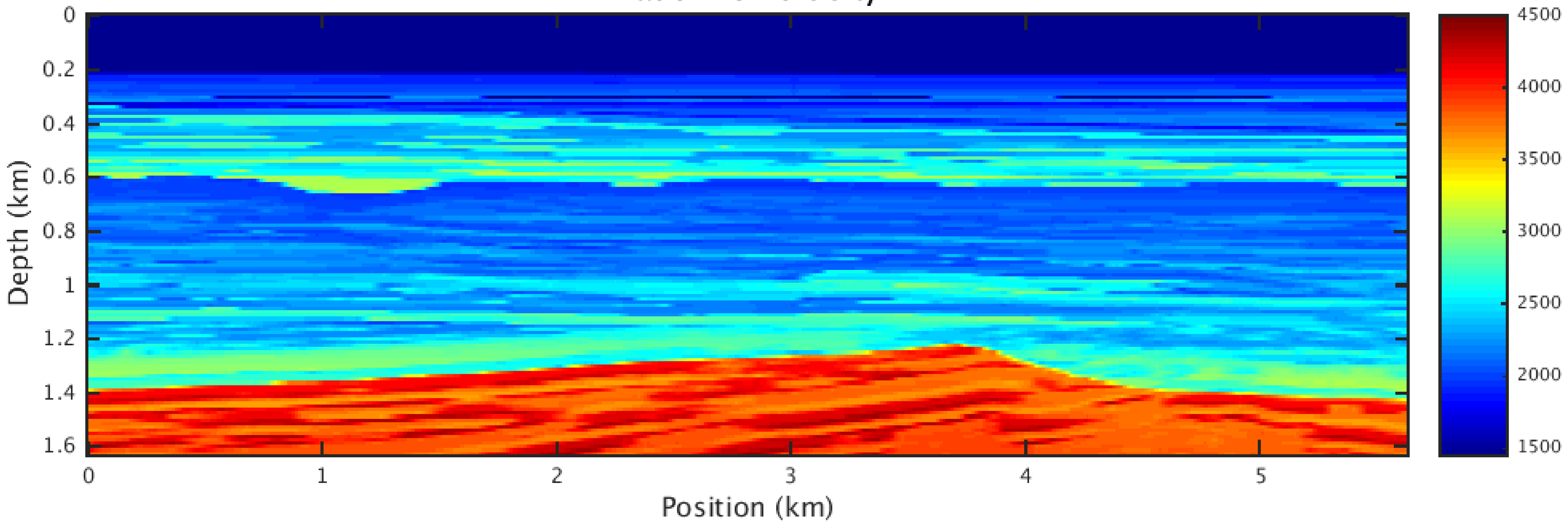
where

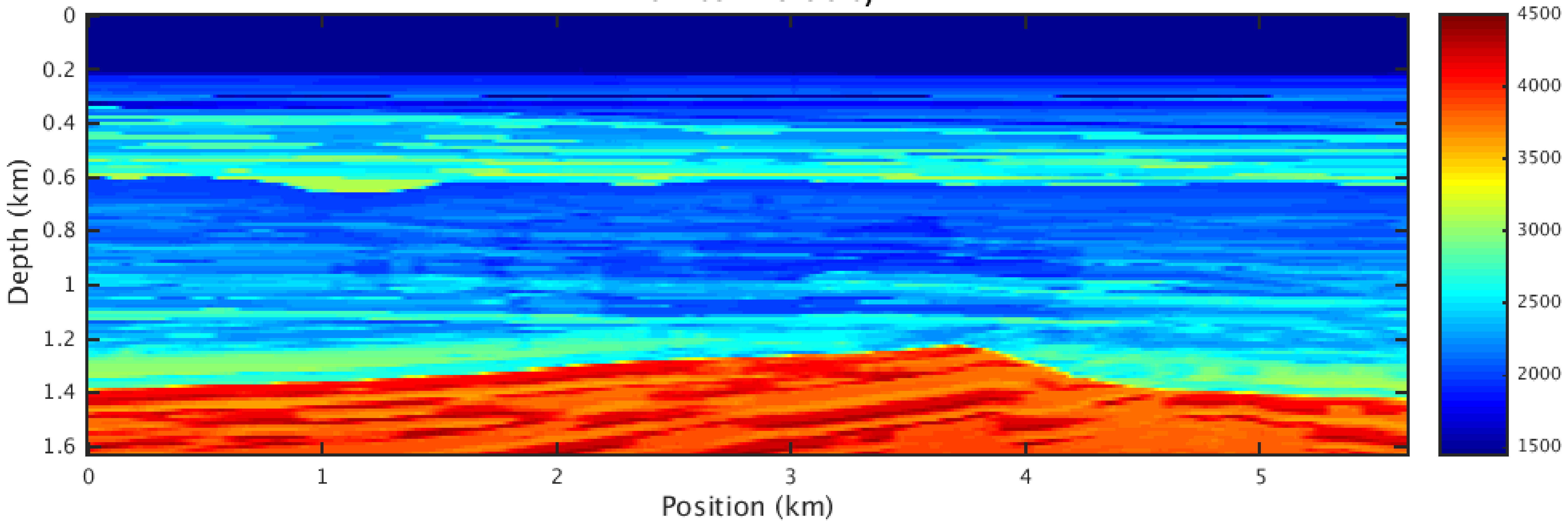
$$\underline{\mathbf{A}} = \mathrm{RM}\mathbf{A}$$

$$\underline{\mathbf{b}} = \mathrm{RM}\mathbf{b}$$

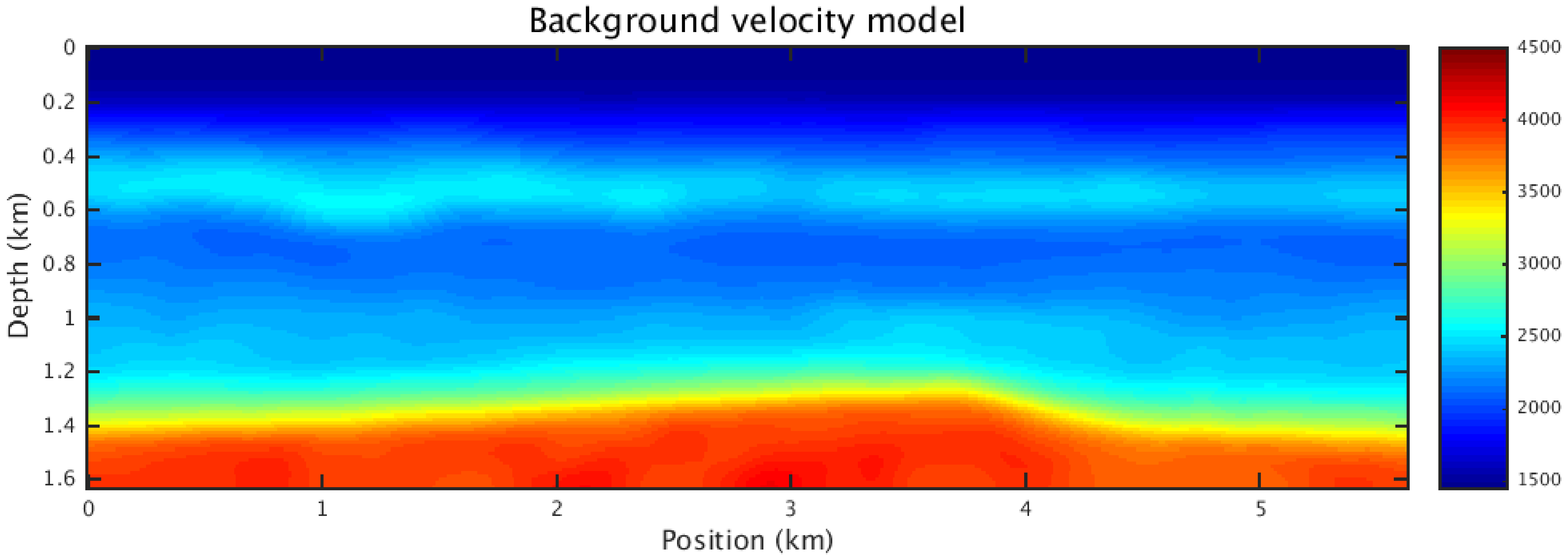
$$\delta\tilde{\mathbf{m}} = \mathbf{C}^H\tilde{\mathbf{x}}$$

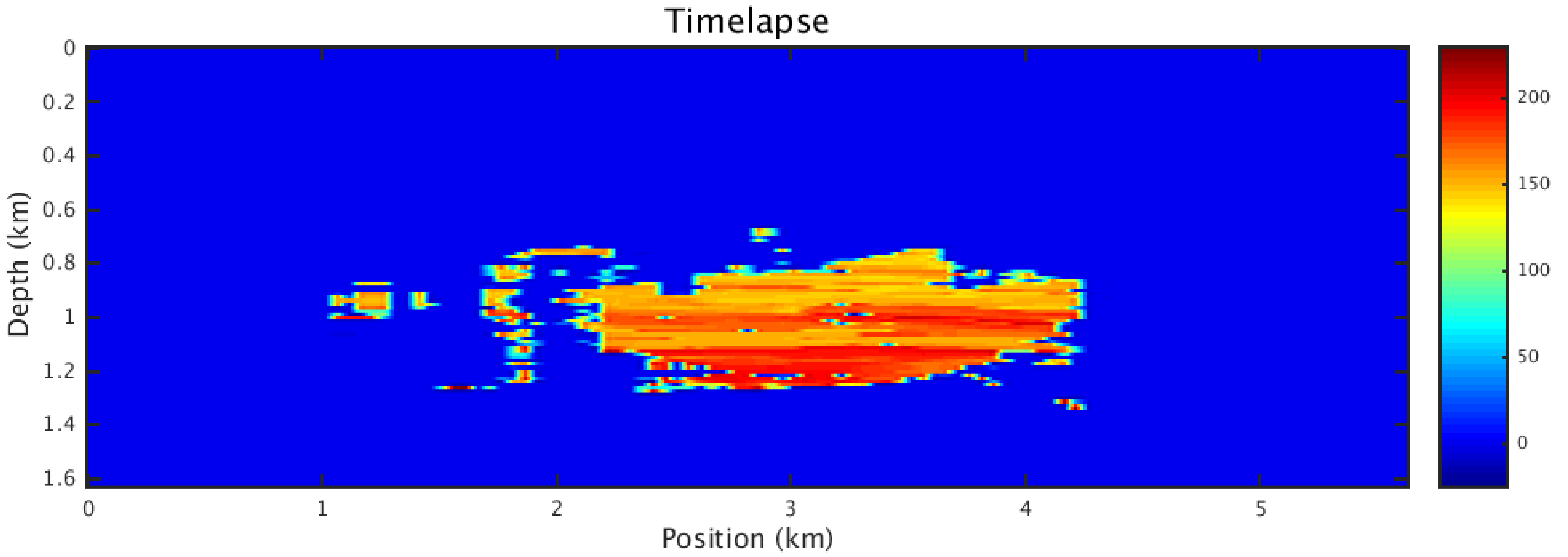
Model


Baseline velocity


Monitor velocity

Initial/Difference


Background velocity model


Timelapse

Migration

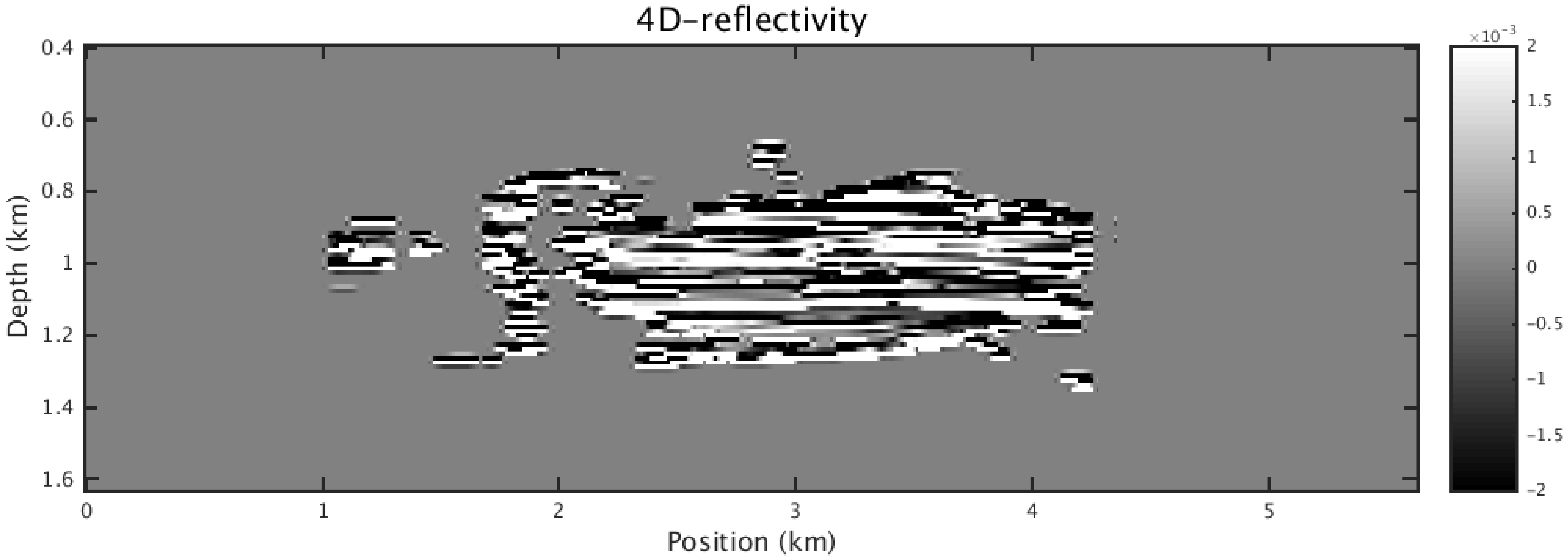
Modeling parameters

- 113 shots @ approx. 50m interval
- 113 receivers @ approx. 50m interval
- 80 frequencies between 3 & 20Hz for imaging
- Shot records of 4seconds
- Ricker wavelet @ 15.0Hz
- Baseline & Monitor with “different” source/receiver positions

Objective

- Imaging of baseline/monitor
- Observe and interpret changes in reflectivity
- Using the independent (IRS) and the joint method (JRM)

Time-lapse reflectivity



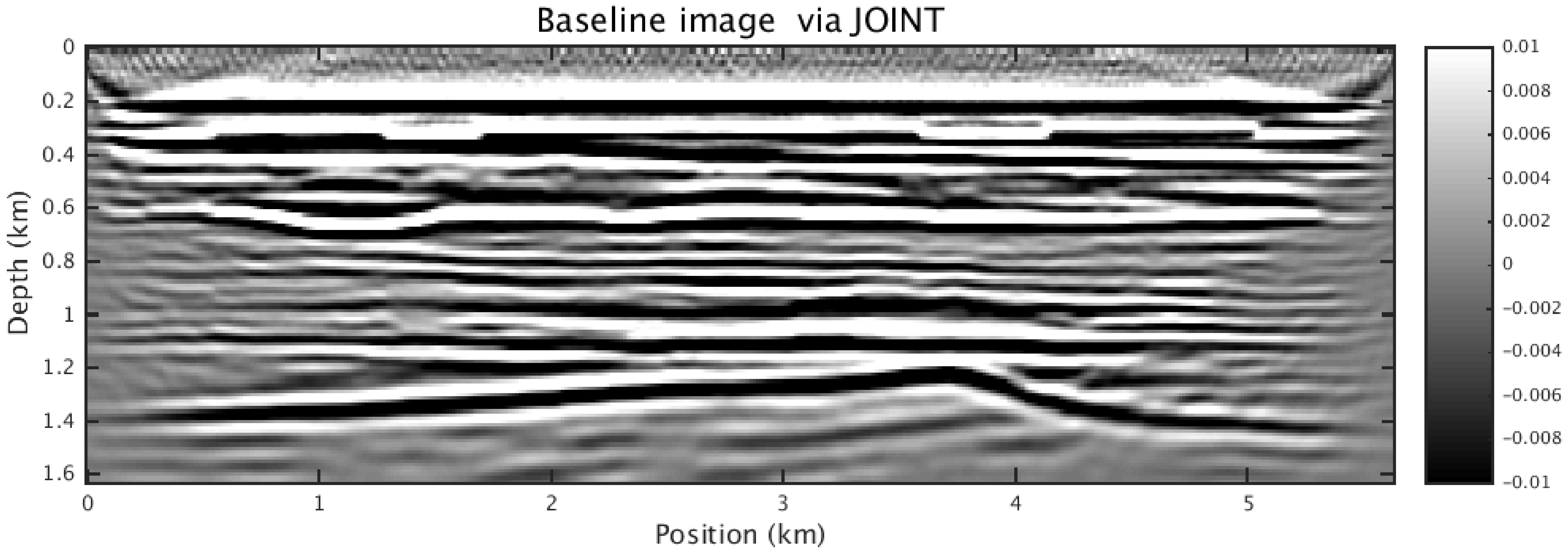
Migration

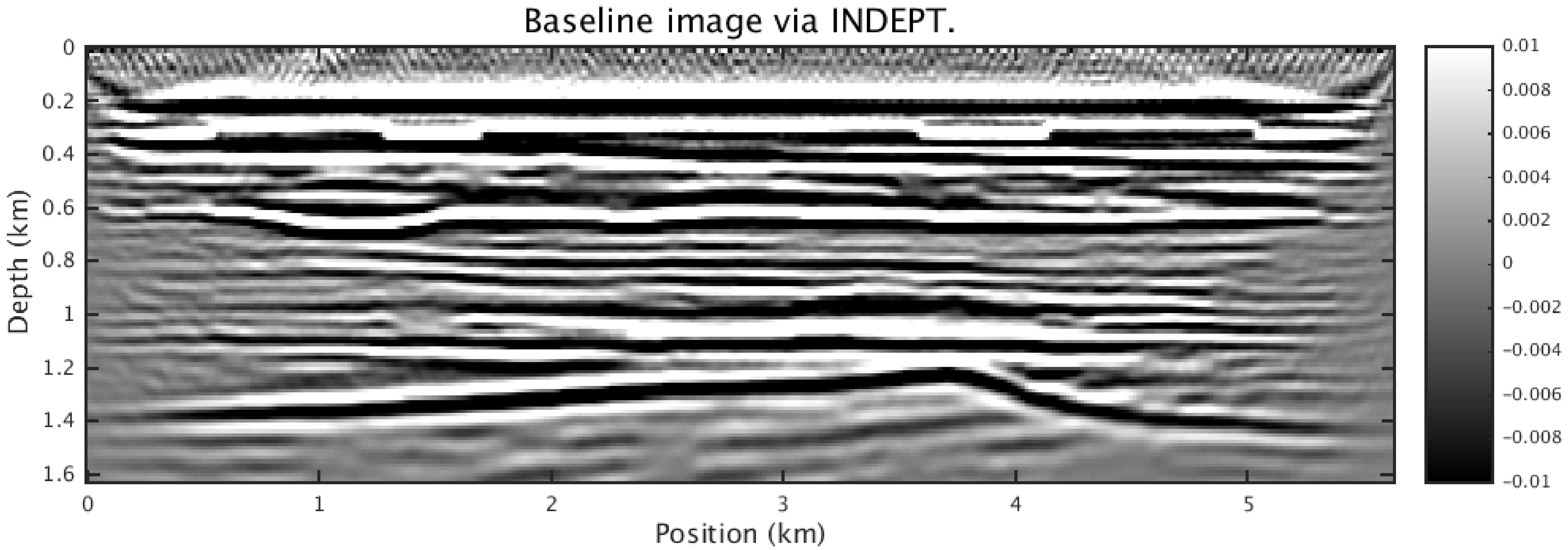
Imaging step

- Randomly select 20 sources and 16 frequencies at each iteration
- Allow renewal of sources/frequencies at each iteration
- Total iteration equivalent to one RTM
- Exploit sparsity (in curvelet domain) of reflectivity
- Ricker wavelet @ 15.0Hz
- Fairly accurate background velocity model

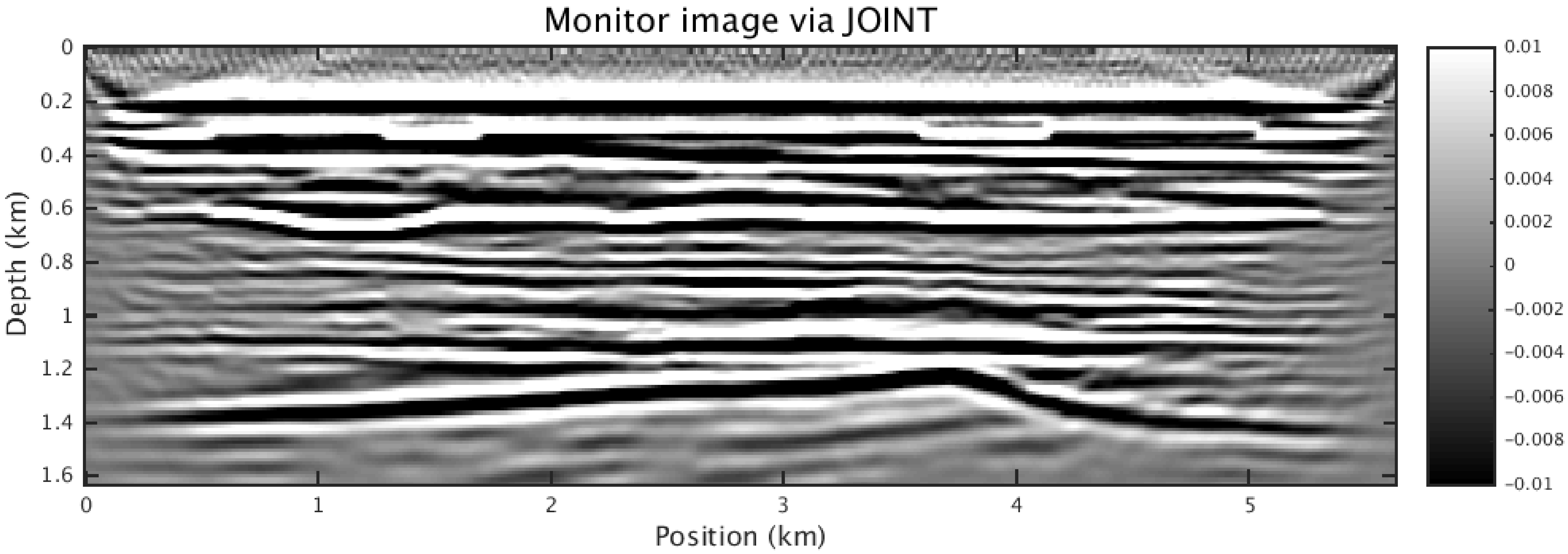
Imaging with correct velocity model for baseline/monitor

Baseline


Baseline image via JOINT
Depth (km)
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
Position (km)
0
1
2
3
4
5
0.01
0.008
0.006
0.004
0.002
0
−0.002
−0.004
−0.006
−0.008
−0.01


Baseline image via INDEPT.
Depth (km)
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
Position (km)
0
1
2
3
4
5
0.01
0.008
0.006
0.004
0.002
0
−0.002
−0.004
−0.006
−0.008
−0.01

Monitor


Monitor image via JOINT
Depth (km)
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
Position (km)
0
1
2
3
4
5
0.01
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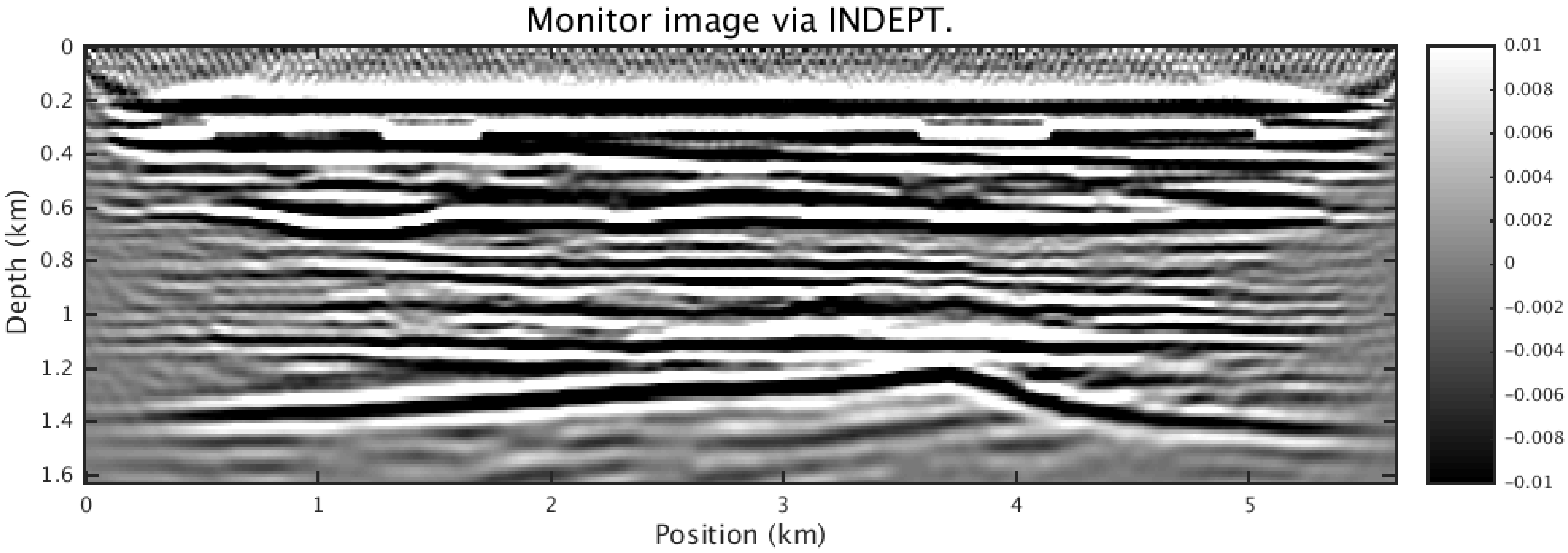
0.006
0.004
0.002
0
−0.002
−0.004
−0.006
−0.008
−0.01


Monitor image via INDEPT.
Depth (km)
0
0.2
0.4
0.6
0.8
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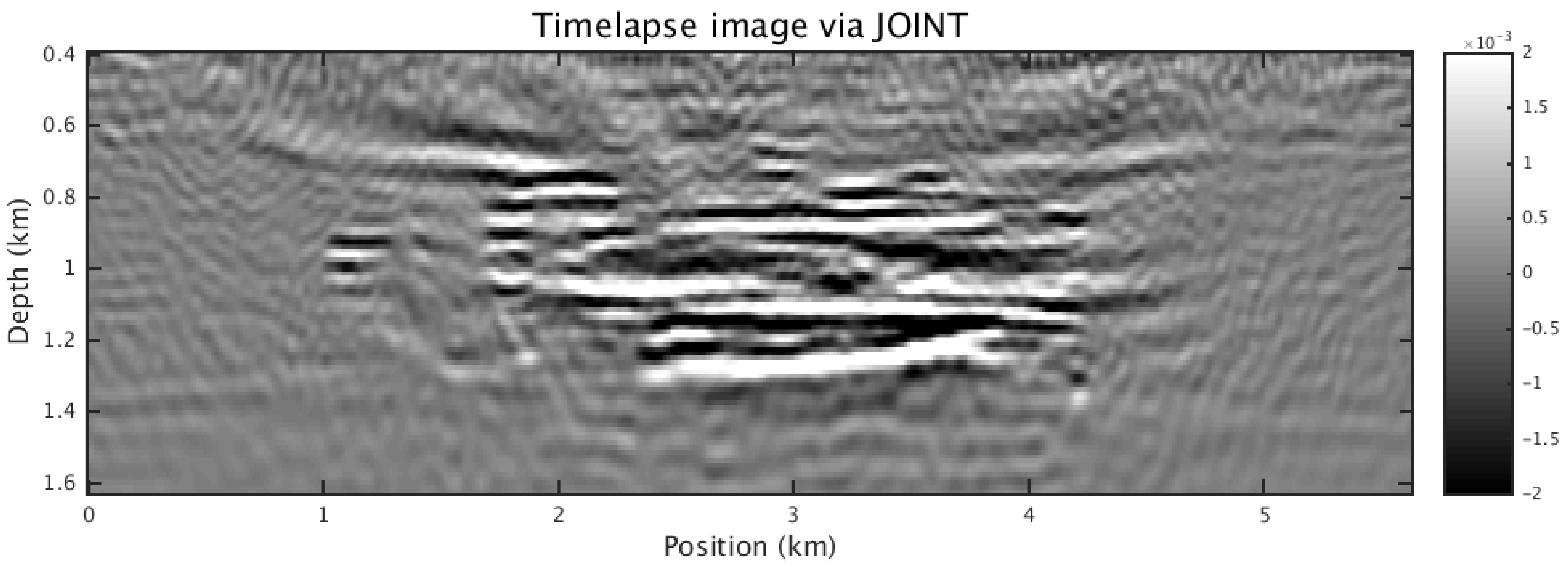
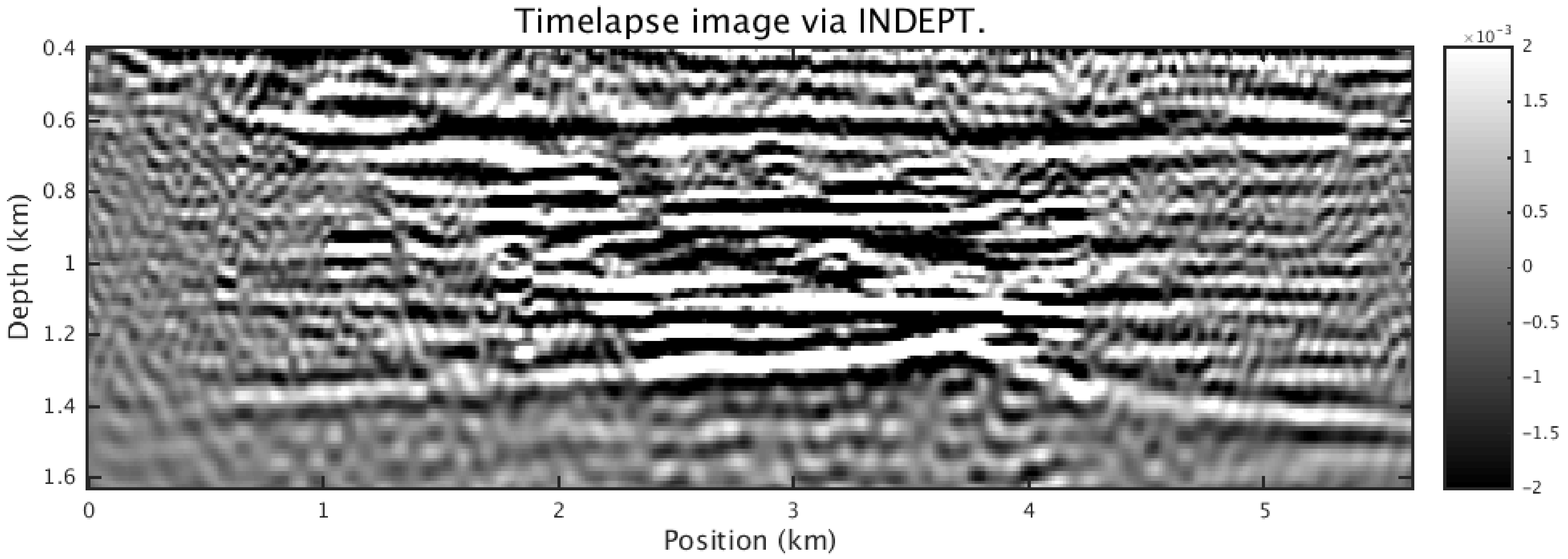
1.2
1.4
1.6
Position (km)
0
1
2
3
4
5
0.01
0.008
0.006
0.004
0.002
0
−0.002
−0.004
−0.006
−0.008
−0.01

Timelapse


Timelapse image via JOINT
Depth (km)
0.4
0.6
0.8
1
1.2
1.4
1.6
Position (km)
0
1
2
3
4
5
$\times 10^{-3}$
2
1.5
1
0.5
0
−0.5
−1
−1.5
−2


Timelapse image via INDEPT.
Depth (km)
0.4
0.6
0.8
1
1.2
1.4
1.6
Position (km)
0
1
2
3
4
5
$\times 10^{-3}$
2
1.5
1
0.5
0
−0.5
−1
−1.5
−2

Conclusions

Randomized sampling techniques may be extended to time-lapse seismic surveys and processing.

Speed-up imaging using random subsets (compressively sampled) of data via sparsity-promotion.

Process time-lapse data jointly, not independently, in order to exploit the *shared* information.

Joint recovery method still fairly stable with respect to slight differences in the background model.

Provided we understand the *physics* of our model, we can reconstruct, process and interpret time-lapse vintages accurately.

Acknowledgements

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