Compressive sensing in marine acquisition and beyond

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thanks to Xiang Li

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Goals

Reduce marine *acquisition* costs by *randomized* dithering

- *shorter* inter shot times & *continuous* recording with *simultaneous* sources

Confront data *explosion* by *randomized* dimensionality *reduction*

- remove IO & PDEs-solve bottlenecks by working on *small subsets* of data (e.g. *supershots*)

Leverage recent developments in *compressive sensing* and *message passing*...

Overarching strategy

Exploit structure

- curvelet-domain *sparsity* of *seismic* data & images

by *randomized* subsamplings that *create*

- *incoherent* and hence *nonsparse* crosstalk/leakage,

which can be removed by *transform*-domain *sparsity* promotion.

Today's topics

Recovery of complete *sequential* marine data from randomized *simultaneous* acquisition

- *compressive sensing* in the *field*

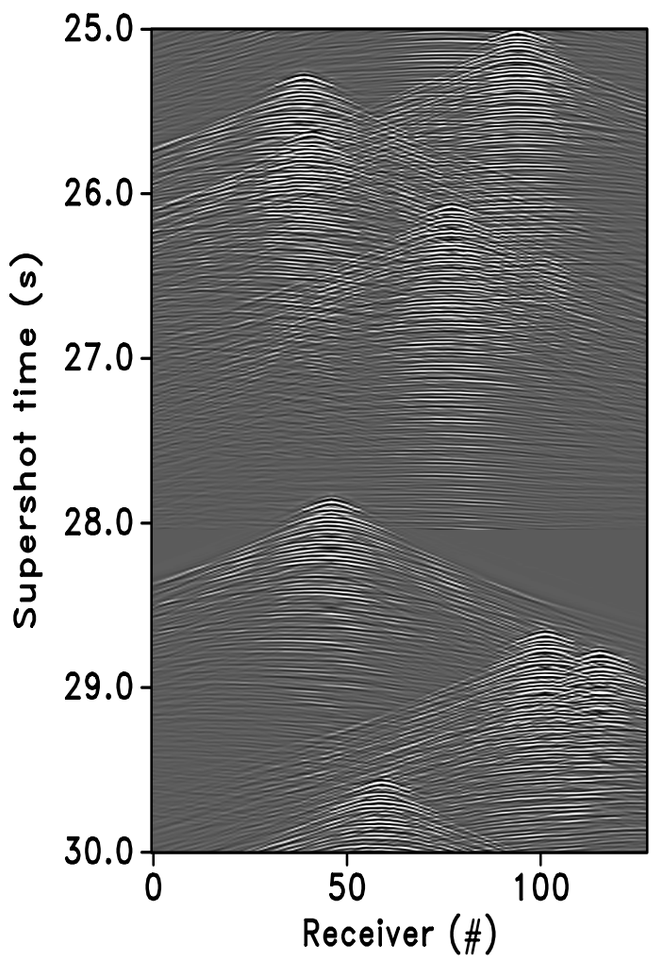
***Only dither: efficient simultaneous marine acquisition* by Haneet Wason, Thursday at 13:55hrs in Room A**

Acceleration of sparsity-promoting *migration* by *message passing*

- *compressive sensing* in the *computer*

***Pass on the message: recent insights in large-scale sparse recovery* by FJH, Wednesday at 10:55hrs in Room B**

Randomized simultaneous marine acquisition



b

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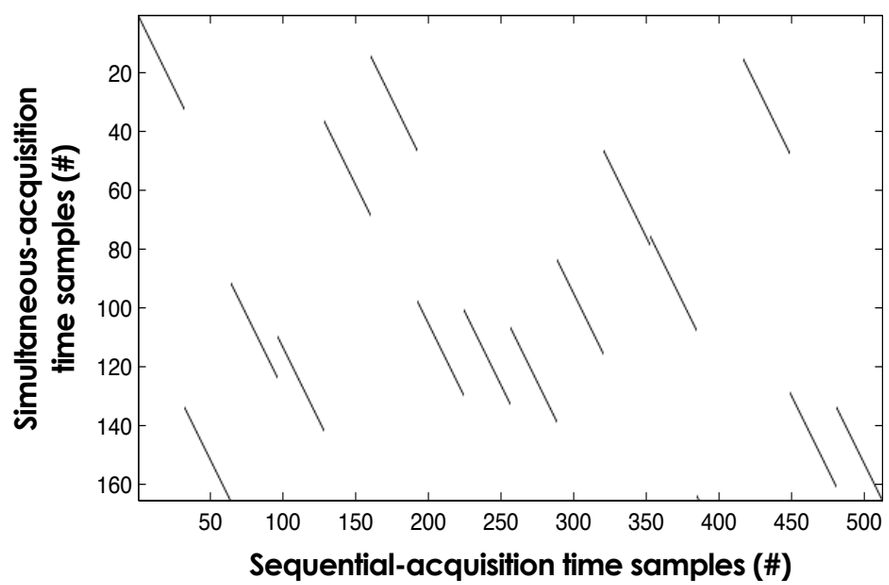
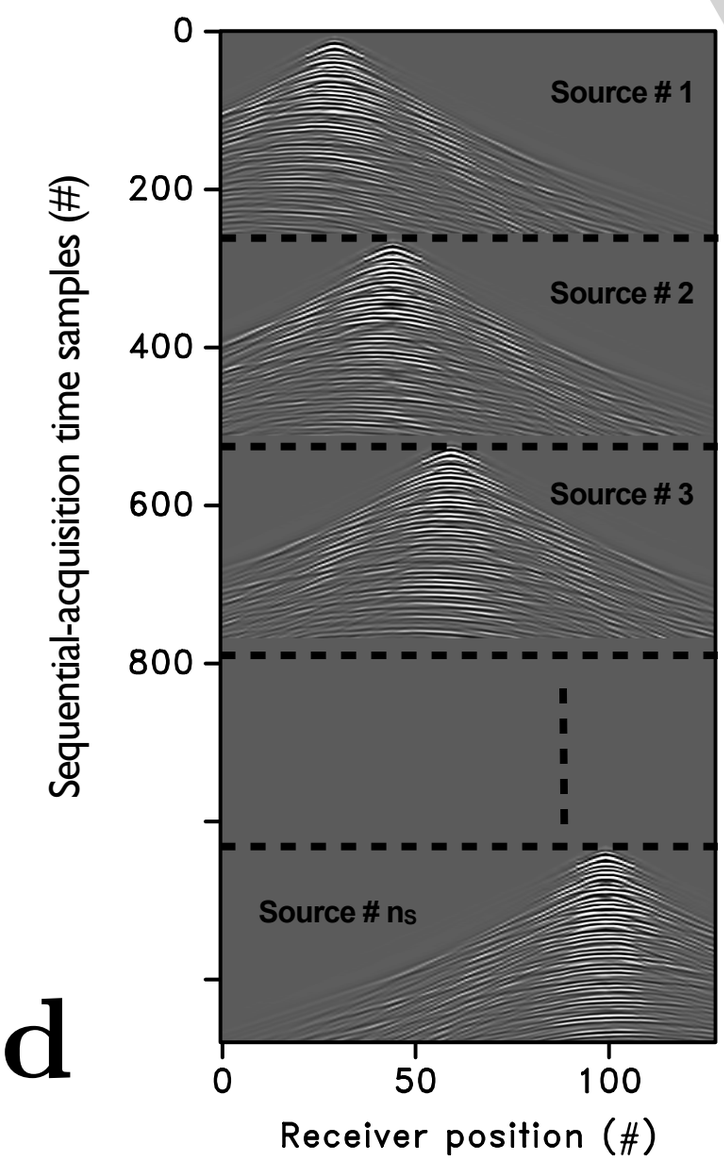


RM



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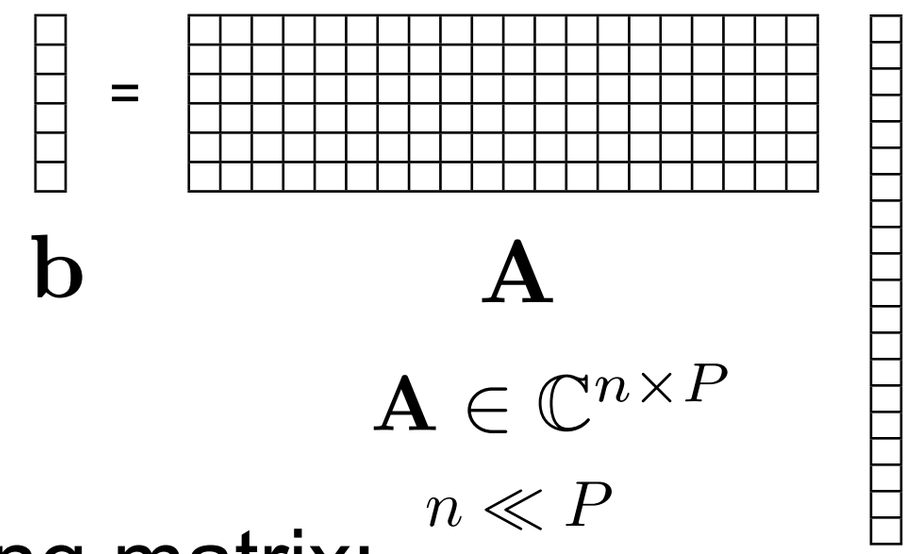
Problem statement

Solve an *underdetermined* system of *linear* equations:

data (measurements /observations)

$\mathbf{b} \in \mathbb{C}^n$



$\mathbf{A} \in \mathbb{C}^{n \times P}$

$n \ll P$

unknown coefficients

$\mathbf{x_0} \in \mathbb{C}^P$

Compressive sensing matrix:

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

Sparse recovery

Sparsity-promoting program:

$$\tilde{\mathbf{x}} = \underbrace{\arg\min_{\mathbf{x}} \|\mathbf{x}\|_1}_{\text{support detection}} \quad \text{subject to} \quad \underbrace{\mathbf{A}\mathbf{x} = \mathbf{b}}_{\text{data-consistent amplitude recovery}}$$

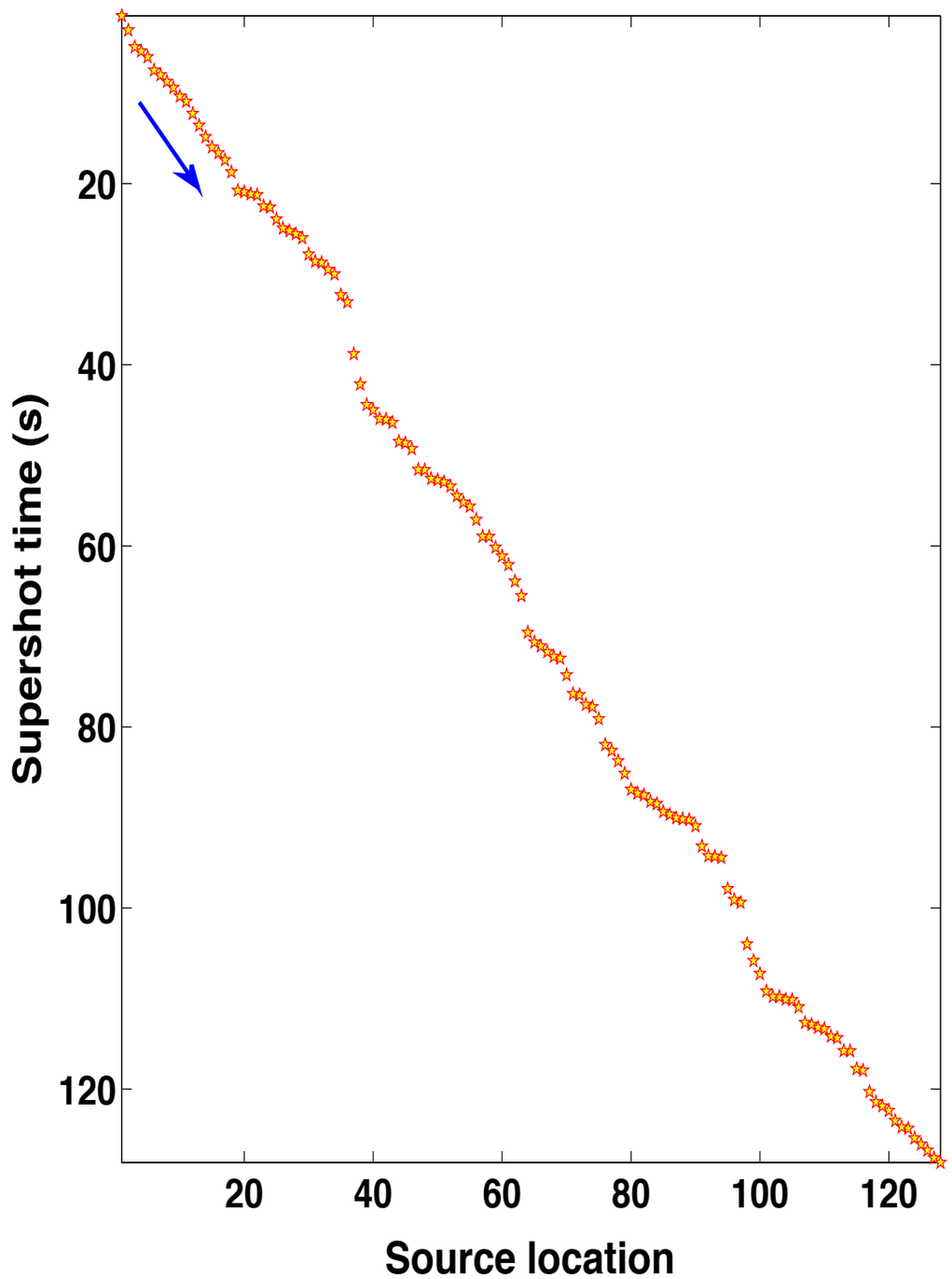
Sparsity-promoting solver: $\mathbf{SPG}\ell_1$ [van den Berg and Friedlander, 2008]

Recover single-source prestack data volume: $\tilde{\mathbf{d}} = \mathbf{S}^{\mathbf{H}}\tilde{\mathbf{x}}$

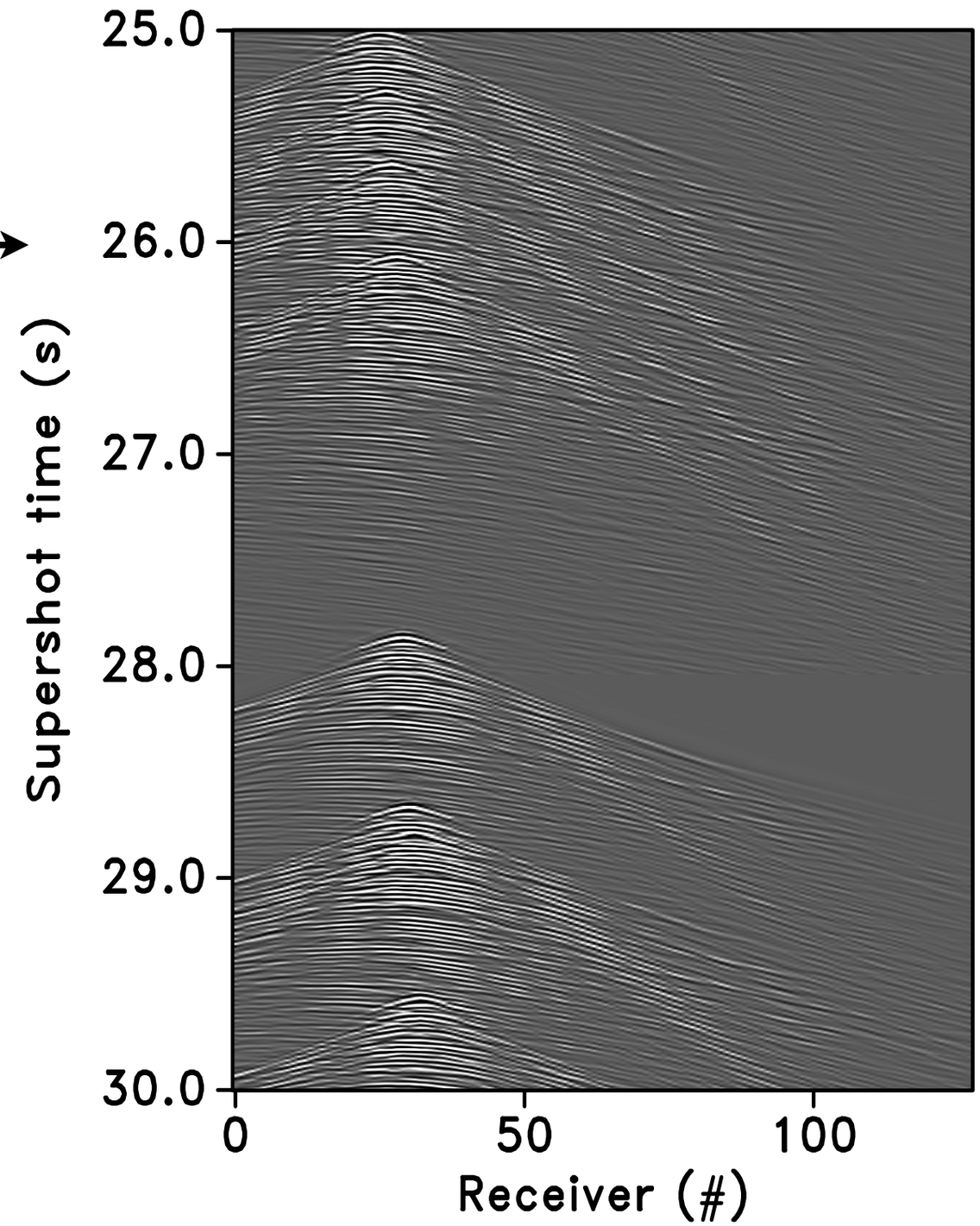
Randomization favors *sparse* recovery by rendering *leakage* into *incoherent* Gaussian noise...That's the hope in practice...

Random time dithering

Acquisition scheme



measurements



Recovery

[from 2X accelerated acquisition]

Conventional processing

Apply the adjoint of the sampling operator

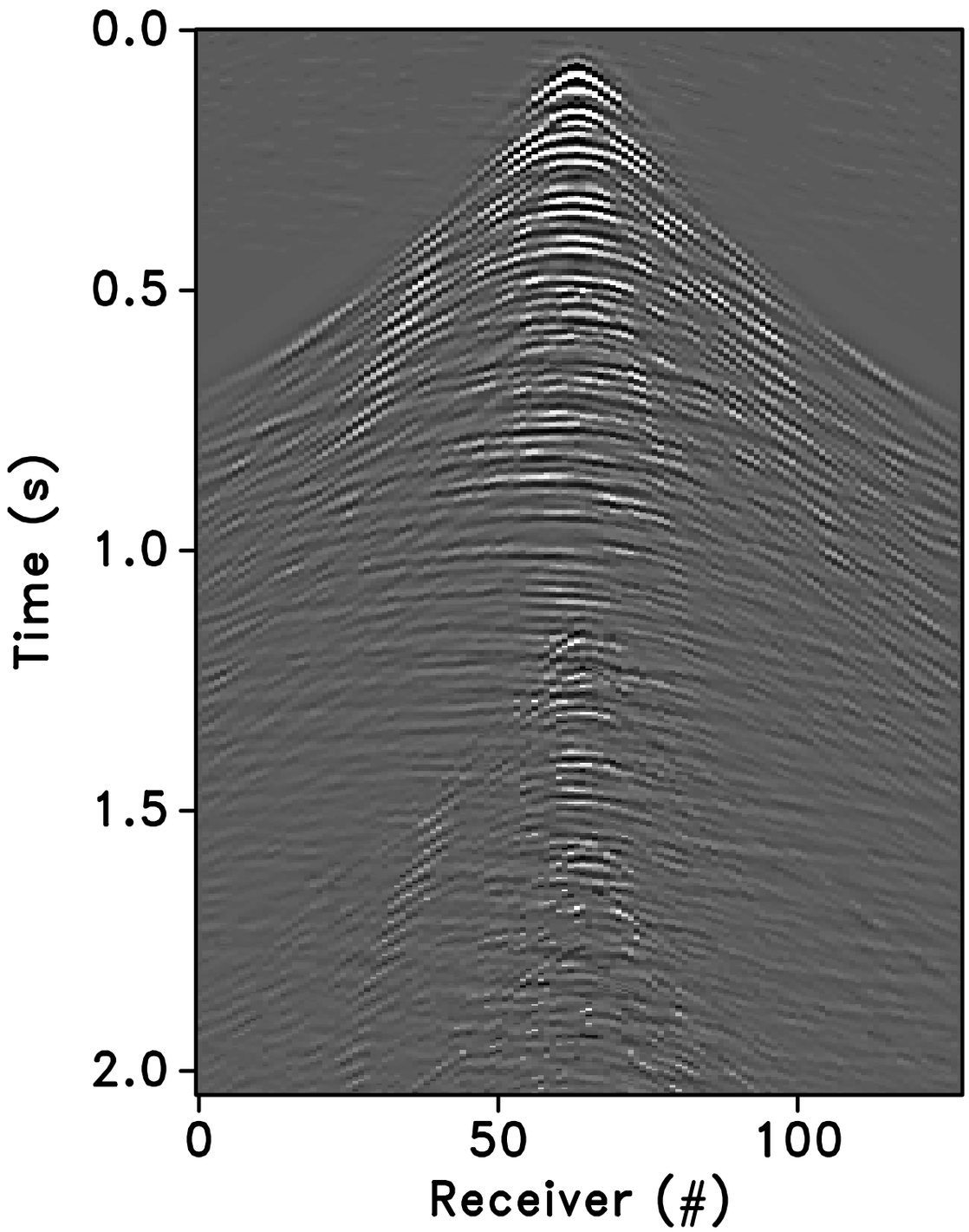
+

Median filtering in the midpoint-offset domain

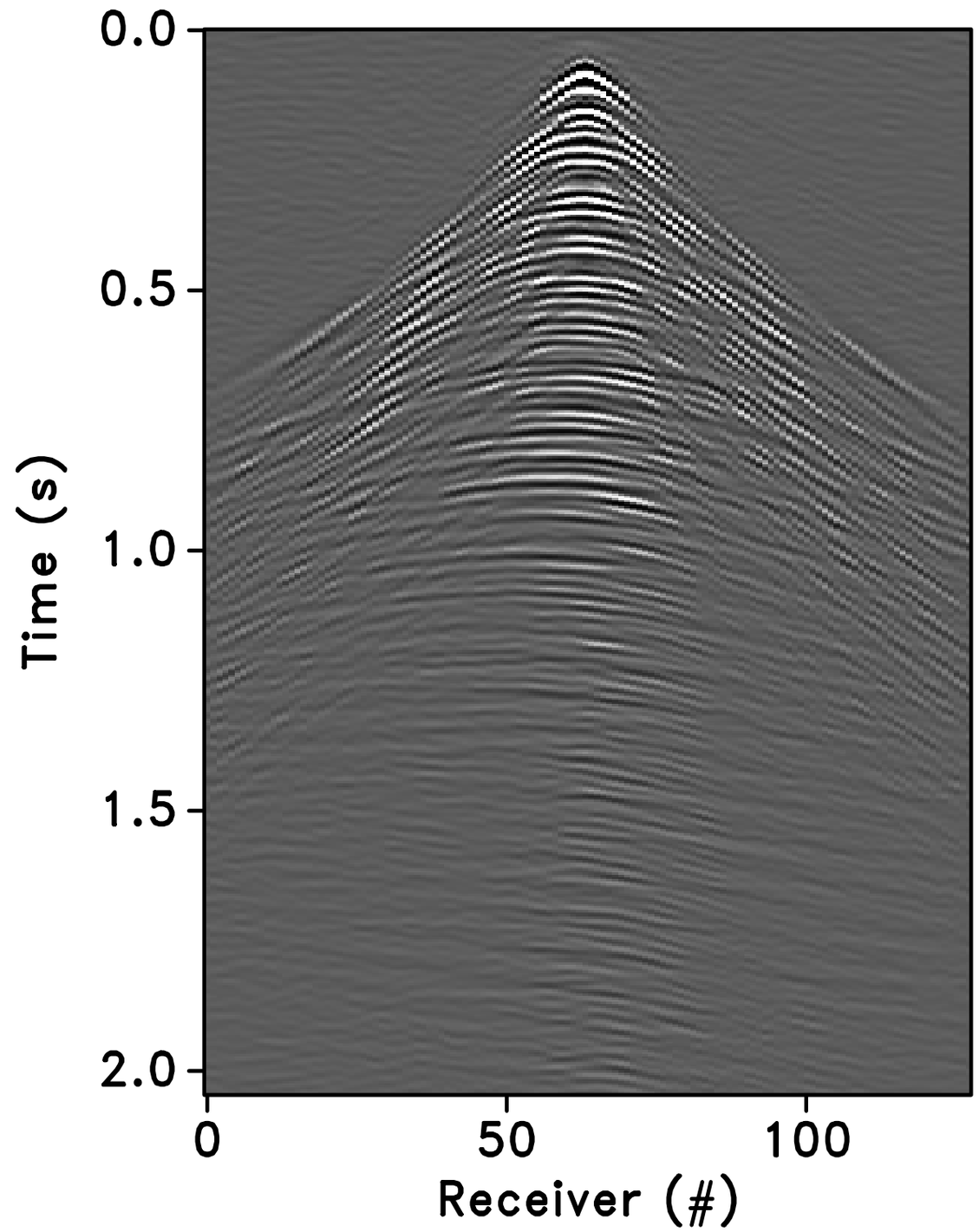
Curvelet-domain sparsity-promotion

Solve an optimization problem (e.g., one-norm minimization)

Conventional recovery : 3.92 dB



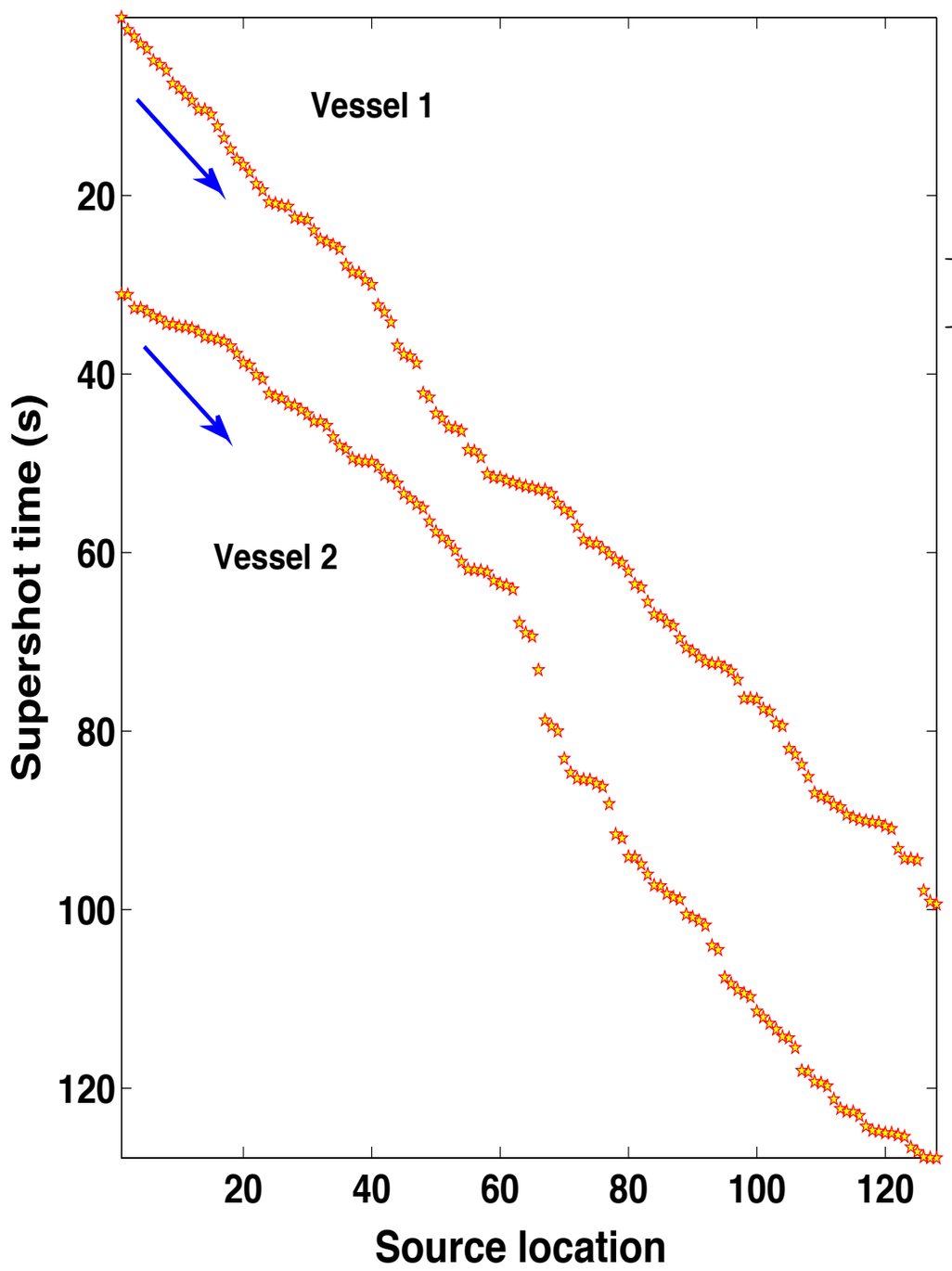
Sparsity-promoting recovery : 8.06 dB



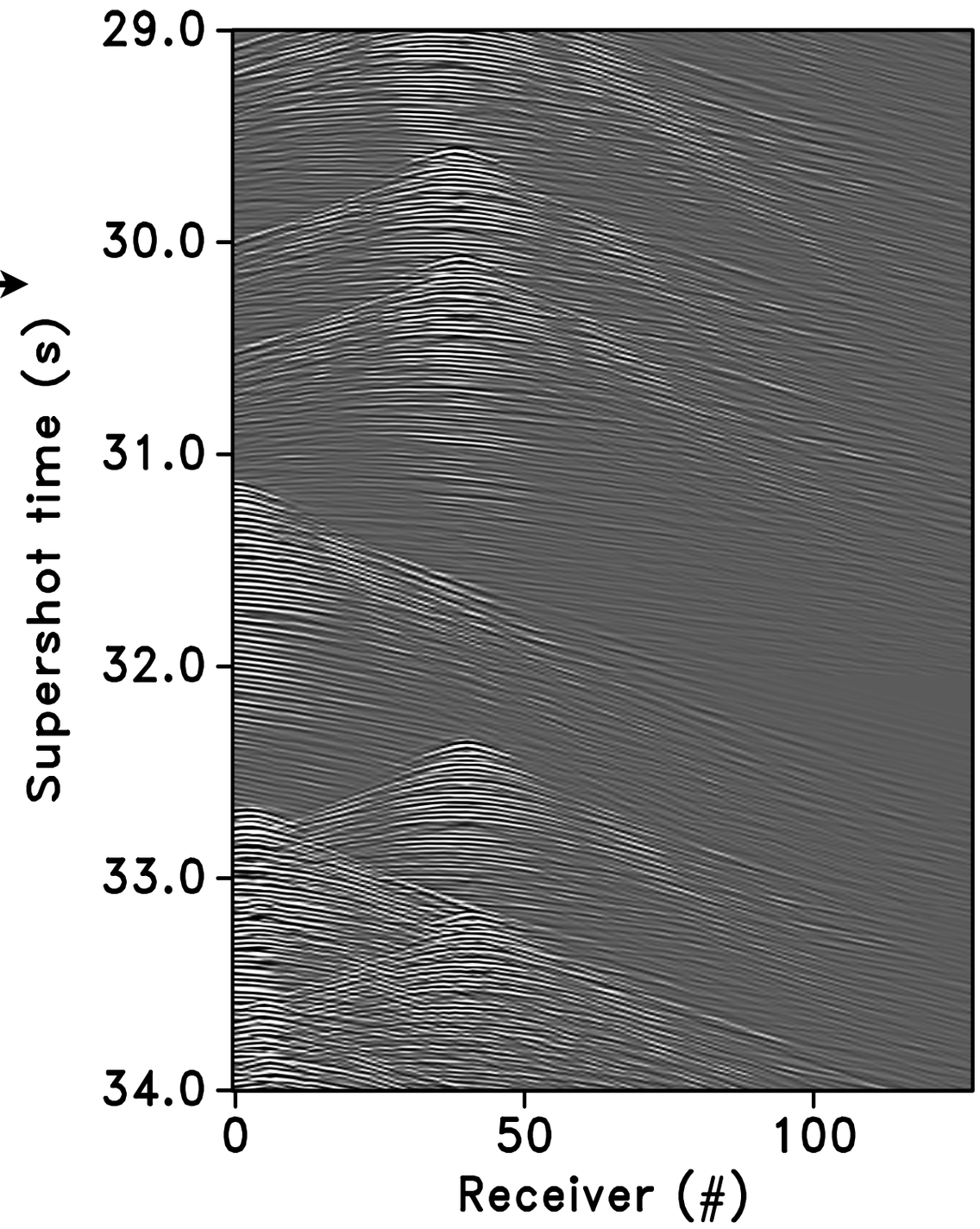
Random time dithering

[2 source vessels]

ACQUISITION SCHEME

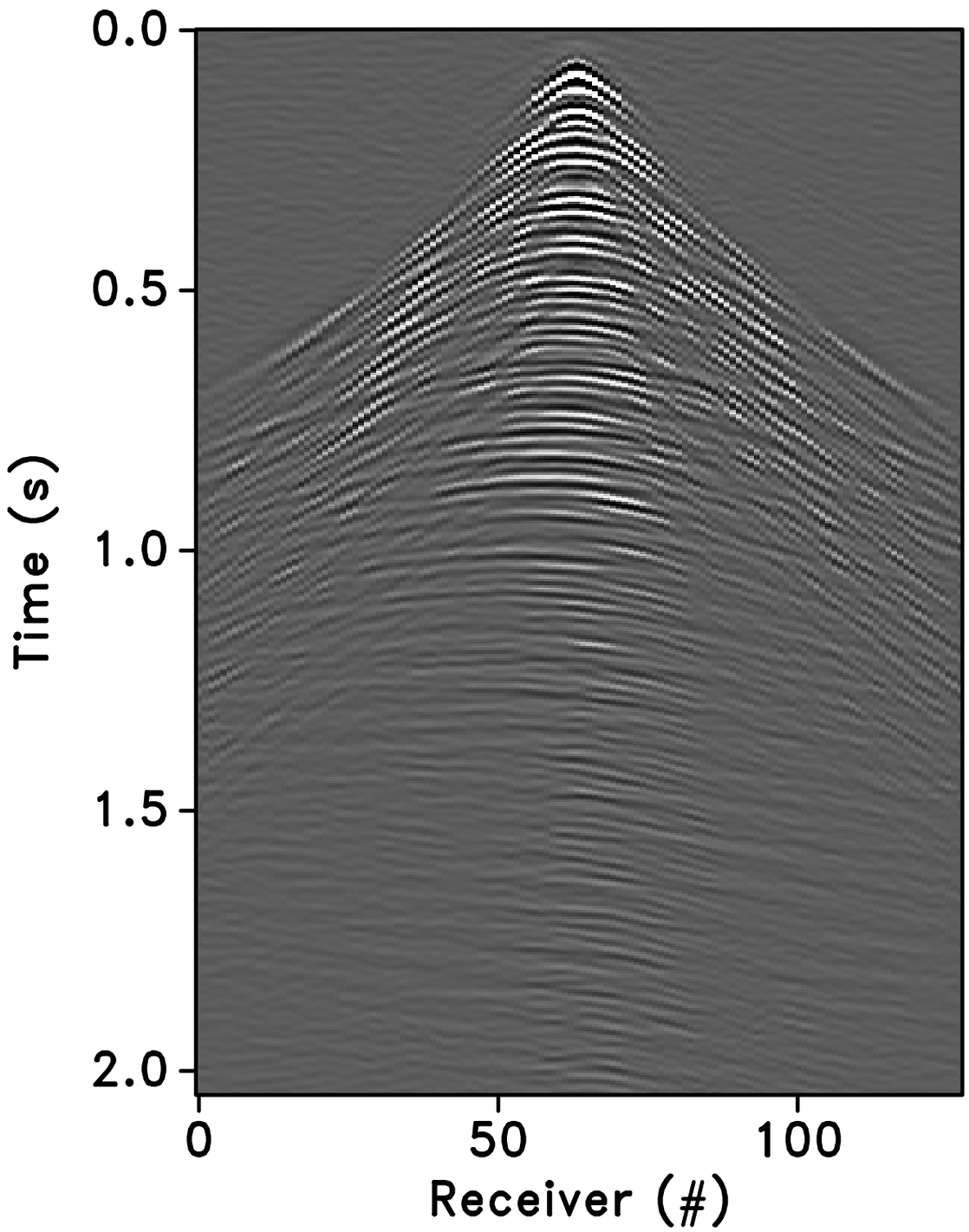


MEASUREMENTS

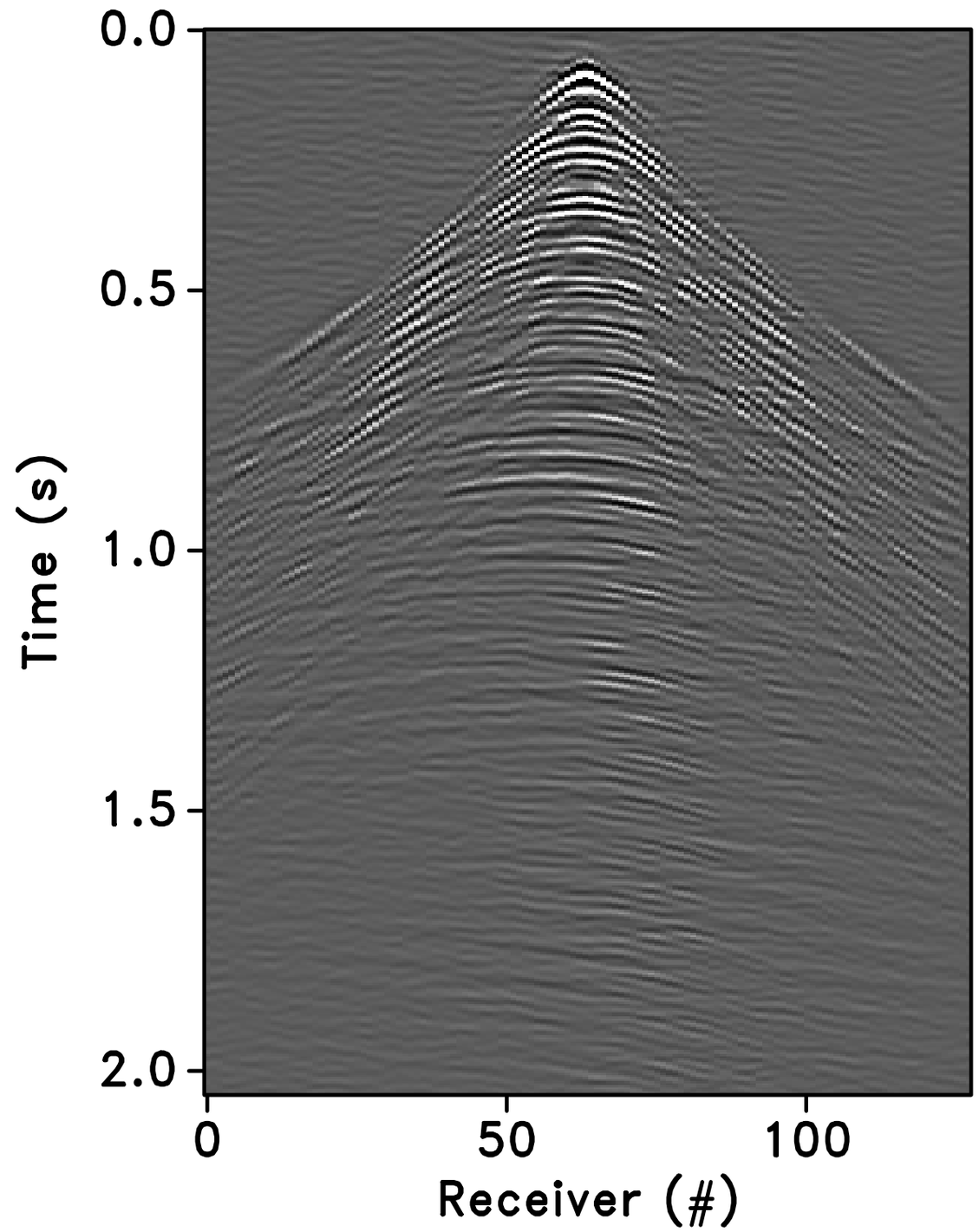


Sparsity-promoting recovery

1 source vessel : 8.06 dB



2 source vessels : 10.3 dB



Observations

Acquisition costs *reduced* by *randomization*

- via *multiple* randomly *dithered* sources

Cost *reduction* at the *cost* of *solving* large-scale *sparsity-promoting* program

- *dominated* by *sparsifying* transform, which is $\mathcal{O}(n \log n)$

We ***win*** because *processing* costs << *acquisition* costs

- processing *turn-around* times may be an *issue*

Big data

http://www.newschool.edu/uploadedImages/events/lang/Data%20Deluge%20compressed(2).jpg

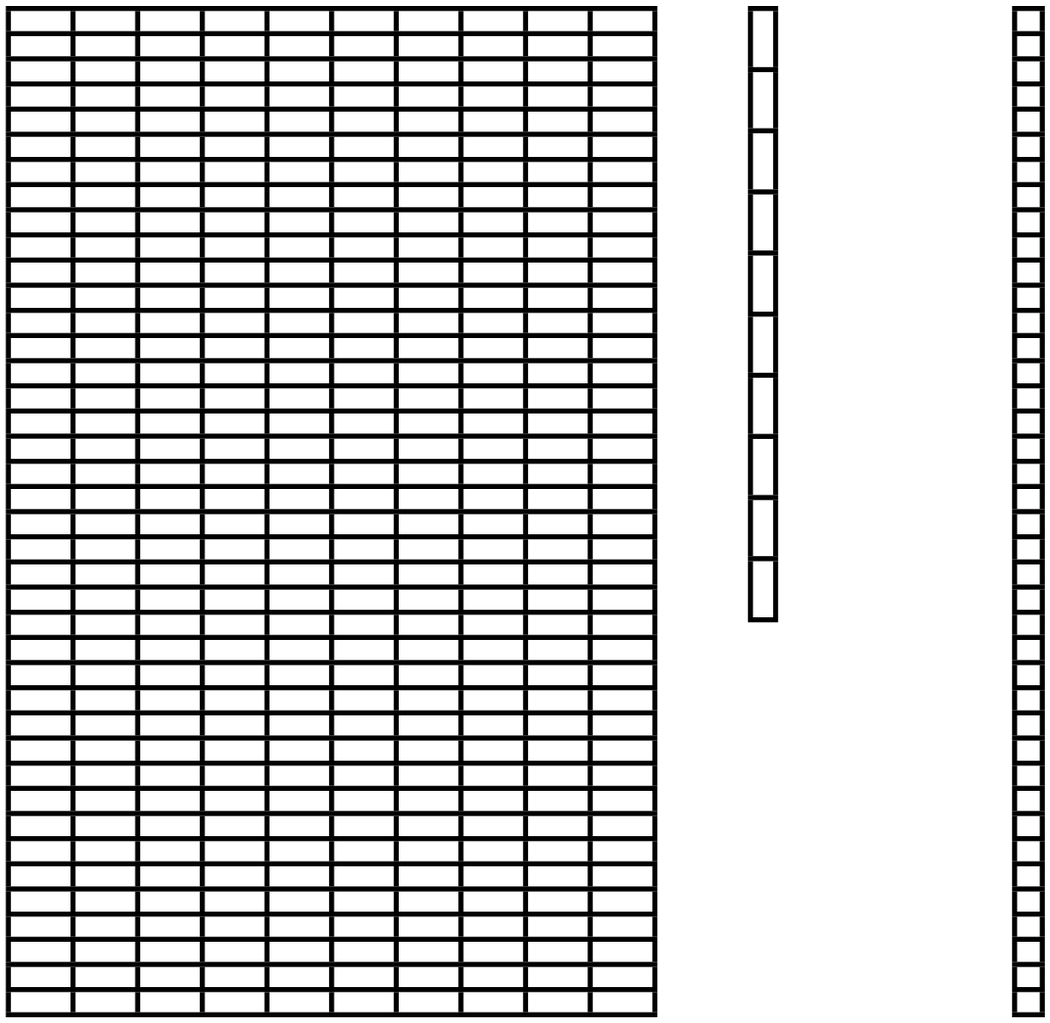
"We are drowning in data but starving for understanding" USGS director Marcia McNutt

"Got data now what" Carlsson & Ghrist SIAM

http://bigdatablog.emc.com/wp-content/uploads/2012/03/gotbigdata.png

Current imaging paradigm

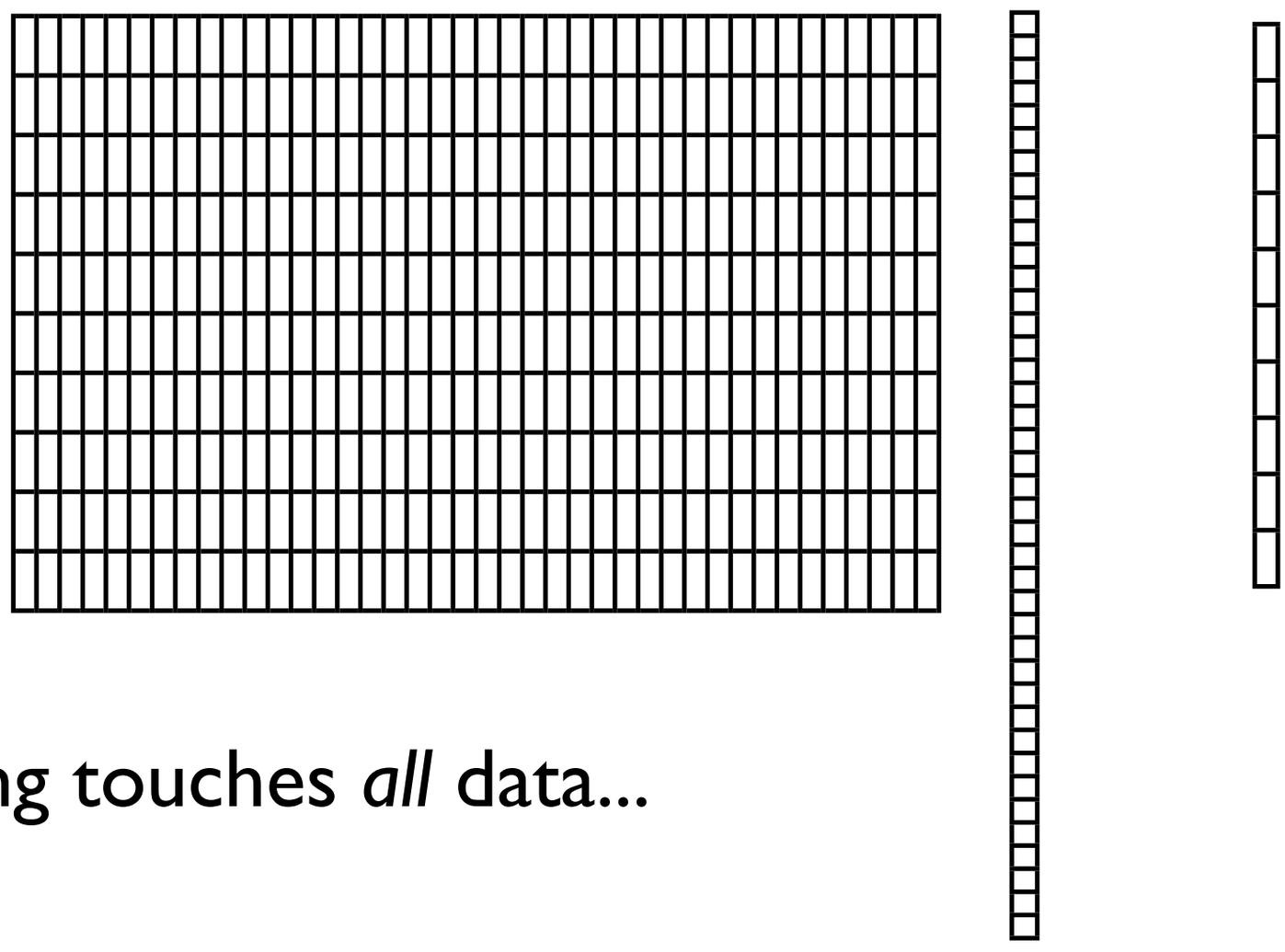
Linear forward model: **A** **x** = **b**



tall matrix
(*all* data)

Current imaging paradigm

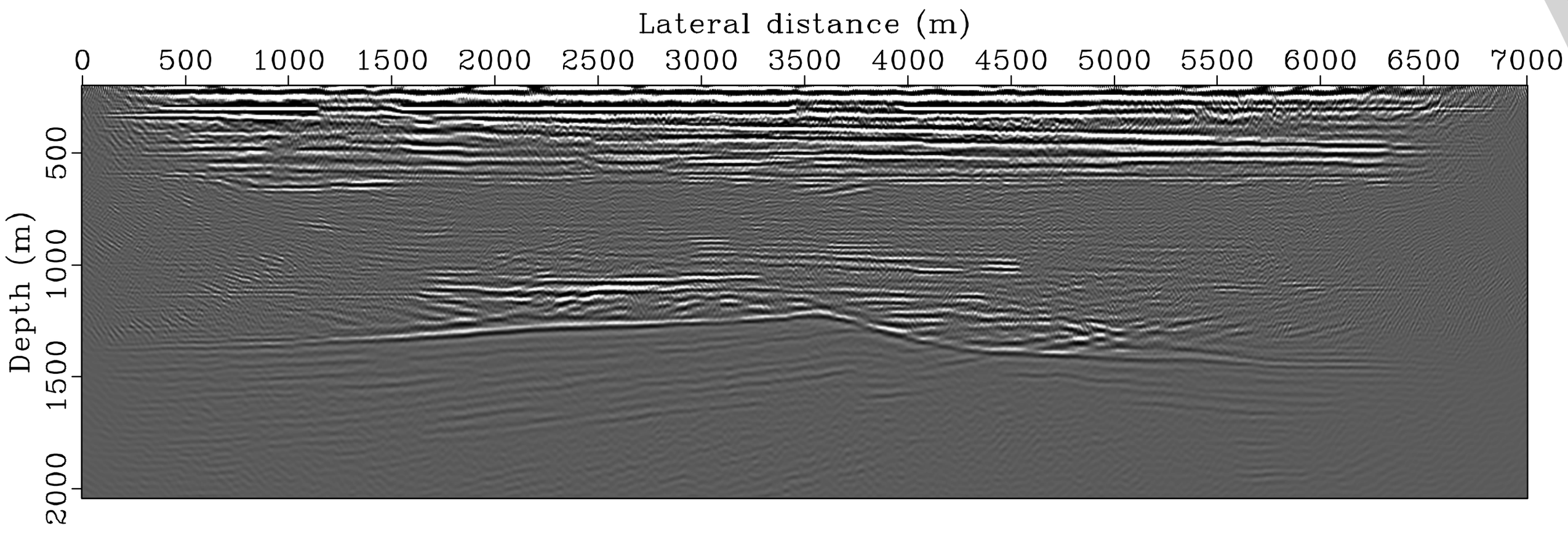
Imaging: $\mathbf{A}^H \quad \mathbf{b} = \mathbf{x}_{\text{migrated}}$



Matched filtering touches *all* data...

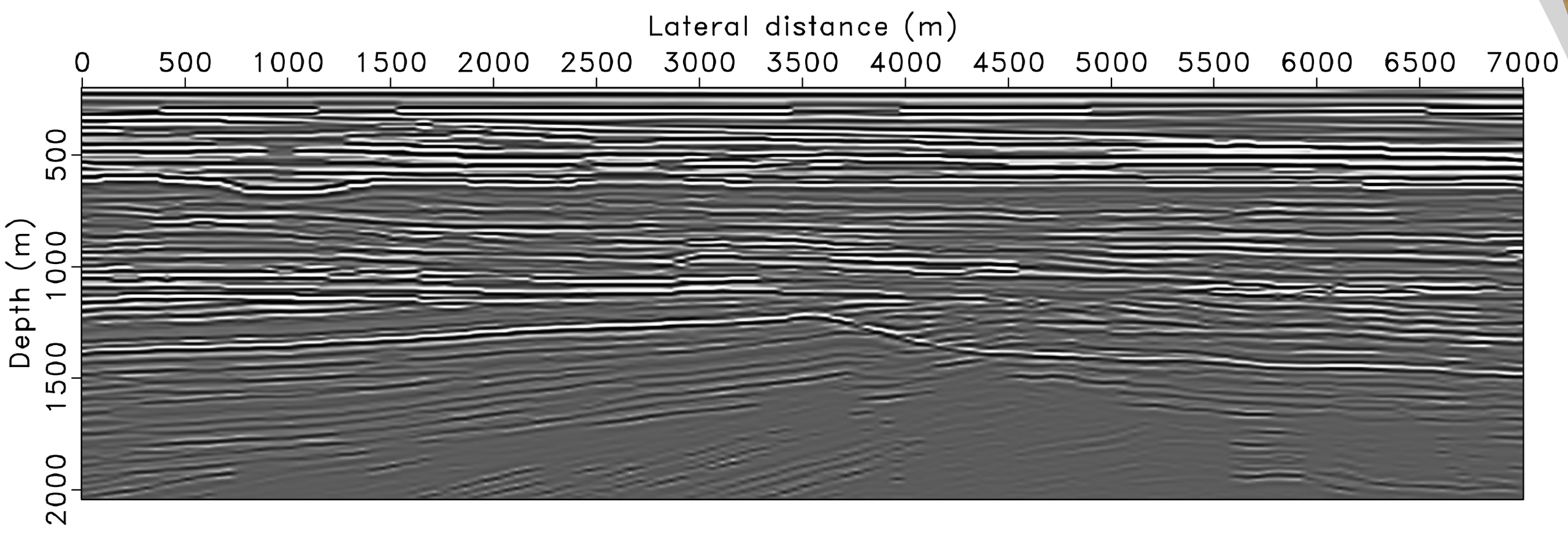
Migration results

[migration with *all* data]



Migration results

[*true* perturbation]



Costs

Computational costs *dominated* by min(# *sources*, # *receivers*)

- PDE solves are *expensive*, i.e., $n_s n_f n_{iter} \mathcal{O}(n^3)$

IO *dominated* by # *sources* X # *receivers*

Renders *iterative* methods computationally *infeasible*

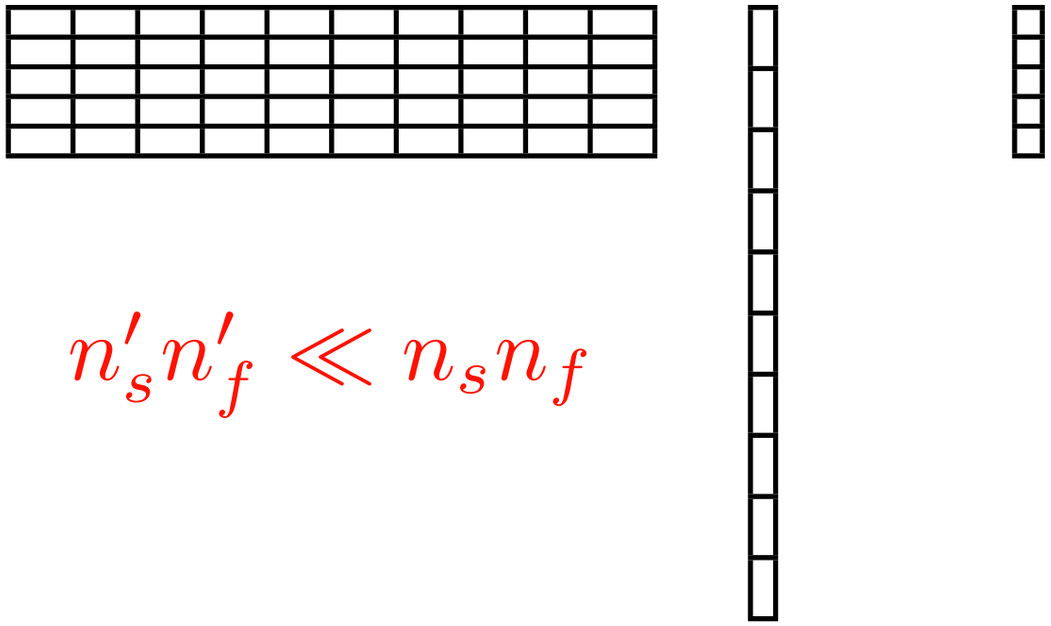
Solution: Reduce # shots & # frequencies

- random *superposition* of shots (supershots)
- random *selection* of shots (marine)
- remove *crosstalk/leakage* by *sparsity* promotion

New paradigm

Invert underdetermined system: **A** **x** = **b**

wide matrix
(*randomized supershots*)



$$n'_s n'_f \ll n_s n_f$$

with *sparsity* promotion.

Challenge

R*eduction* at the *cost* of *solving a sparsity-promoting* program

- cost *dominated* by *(de)migrations*, which are *still*

$$n'_s n'_f n_{iter} \mathcal{O}(n^3)$$

We ***loose*** because *optimization* requires too *many* iterations to obtain *high-quality* results

- turn-around times *really* become an *issue*

[Montanari, '12; FJH & Li, '11-'12]

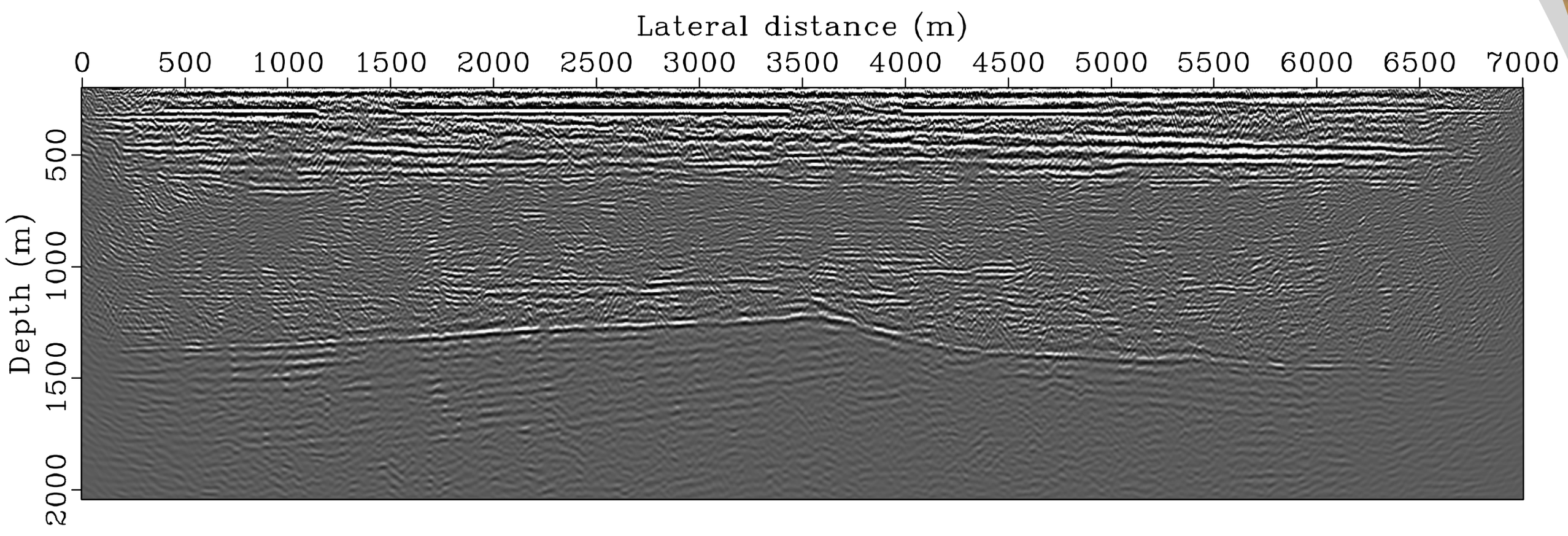
Supercooling

Culprit: Build up of *correlations* between the model *iterate* and *random* source *encoding* slows down *convergence*

Solution: *Rerandomize* by drawing *independent* supershots *after* each *subproblem is solved*

- *breaks correlation* buildup as in message passing
- *minimal* extra *cost*
- *turn* each *subproblem* into a *simple* "denoising" problem

Imaging results
[*without* message passing]

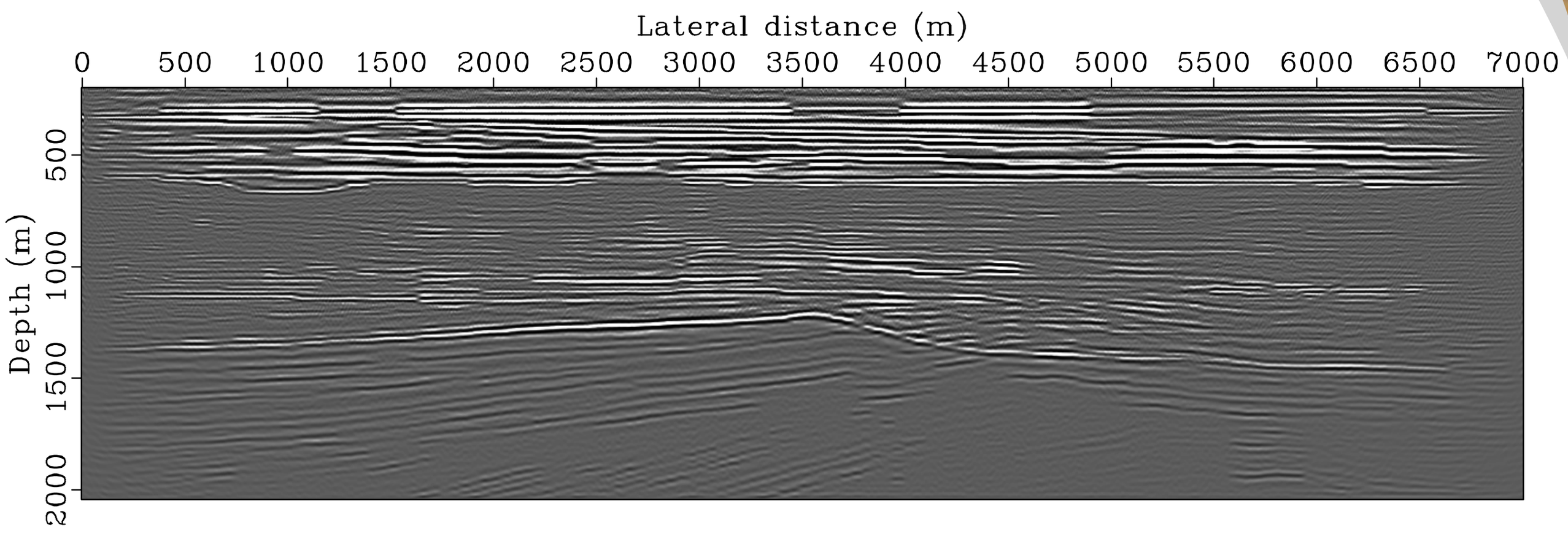


3 *supershots* from 350 shots

10 *random* frequencies from 20Hz-50Hz

Imaging results

[*with* message passing via renewals]



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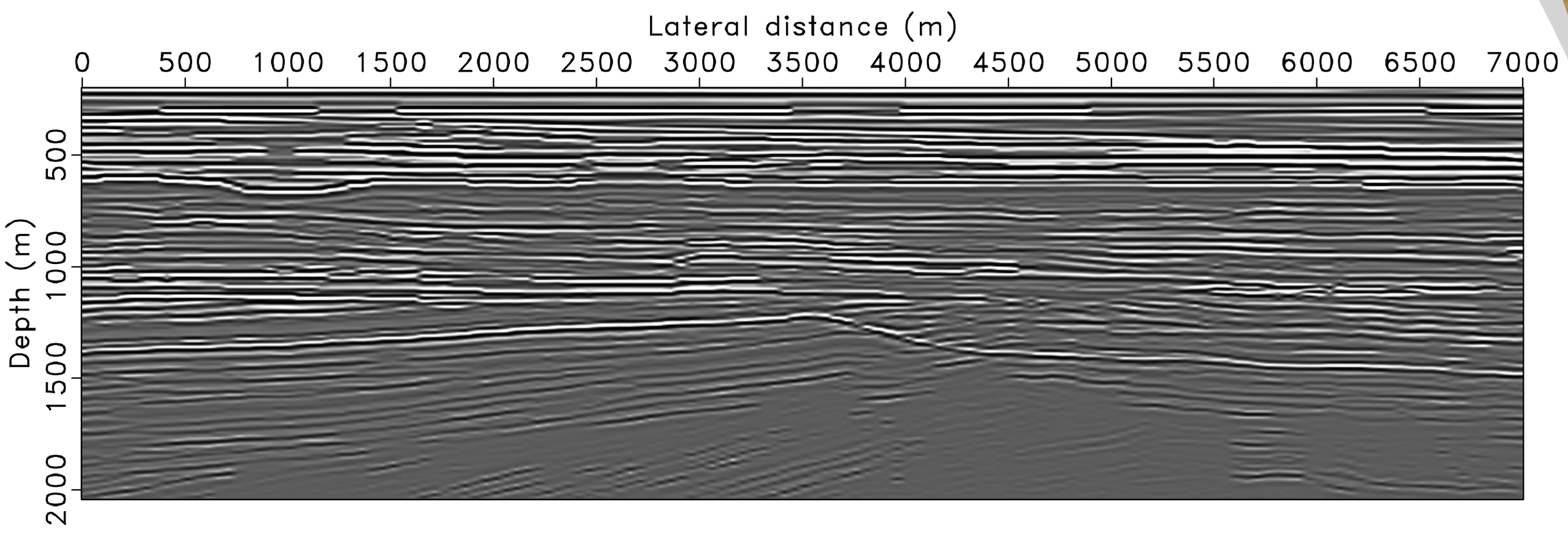
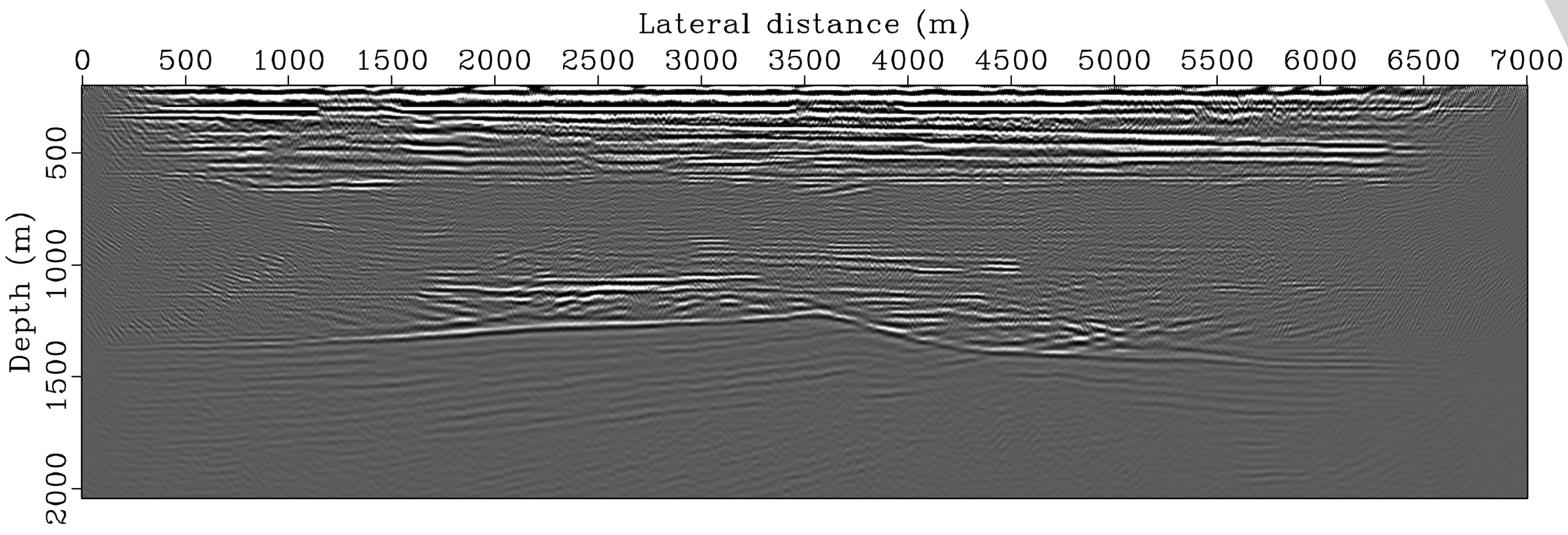
Migration results

[*true* perturbation]



Migration results

[migration with *all* data]



Observations

Randomized simultaneous marine acquisition & *sparsity-promoting* migration with *randomized* source *encoding* are both *instances* of *compressive sensing*

- *efficient* acquisition and *fast* computations
- new *paradigm* in *acquisition* & *inversion* where *reliance* on *full* sampling & touching *all* data has been *removed*
- involves *solution* of *large-scale* optimization problems, which *require fast* solution *strategies* such as message passing...

Challenges

"Data poor" acquisition:

- *engineering* principles for acquisition *design & recovery*
- *calibration & sensitivity* to model space errors

"Data rich" computations:

- *practical* workflows & recovery guarantees
- reliance on *full* sampling

Holy grail: integration of the two approaches...

Acknowledgments

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NSERC CRSNG

Further reading

Simultaneous & continuous acquisition:

- *A new look at simultaneous sources* by Beasley et. al., '98.
- *Changing the mindset in seismic data acquisition* by Berkhout '08.

Simultaneous simulations, imaging, and full-wave inversion:

- *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.
- *Efficient Seismic Forward Modeling using Simultaneous Random Sources and Sparsity* by N. Neelamani et. al., '08.
- Compressive simultaneous full-waveform simulation by FJH et. al., '09.
- Randomized dimensionality reduction for full-waveform inversion by FJH & X. Li, '10
- Fast full-wavefield seismic inversion using encoded sources by Krebs et. al., '09
- *An effective method for parameter estimation with PDE constraints with multiple right hand sides. by* Eldad Haber, Matthias Chung, and Felix J. Herrmann. '10
- Seismic waveform inversion by stochastic optimization. Tristan van Leeuwen, Aleksandr Aravkin and FJH, 2010.
- Efficient least-squares imaging with sparsity promotion and compressive sensing by FJH & Li, '12
- Fast randomized full-waveform inversion with compressive sensing by Xiang Li et. al., '12

Further reading

Compressive sensing & sparse solvers

- Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information by Candes, 06.
- Compressed Sensing by D. Donoho, '06
- Probing the Pareto frontier for basis pursuit solutions by E. van den Berg and M. Friedlander, '08

Message passing

- Message passing algorithms for compressed sensing by David Donoho et. al., 2009
- Graphical Models Concepts in Compressed Sensing by Andrea Montanari, '2012

Thank you

www.slim.eos.ubc.ca