Welcome and overview of SINBAD & DNOISE

Felix J. Herrmann

SLIM

Seismic Laboratory for Imaging and Modeling
the University of British Columbia

Our mission

Development of the *next* generation of seismic data acquisition, processing, imaging, and inversion technology

Dissemination of research findings to *spark* innovations

Training of the next-*generation* of seismologists at

- undergraduate
- graduate, and
- post-graduate level

SINBAD's research team

Highly *interdisciplinary* and able to *leverage* recent developments in

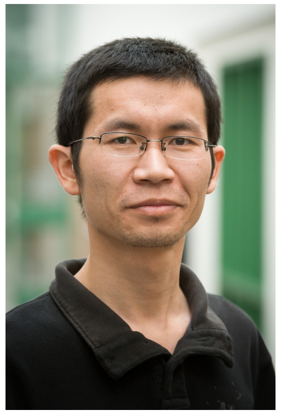
- *exploration* geophysics
- *computer* science (convex/stochastic optimization)
- *mathematics* (compressive sensing)

New additions & visitors

8 *new* graduate students & 1 new PDF

3 long-term visitors

- Professor Dong-Joo Min (Seoul National University)



- Dr Sanyi Yuan (University of Petroleum, Beijing)
- Joost van der Neut (Delft University of Technology)

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Research team

Total of 26 (under)graduate students, PDFs, visitors, faculty, and staff...

Recent collaborations

Mike Warner on wave simulators & FWI (Imperial College)

Ben Recht on large-scale minmax optimization (U. of Wisconsin)

Dan Gordon on Helmholtz preconditioning (University of Haifa)

Funding

Seismic Laboratory for Imaging and Modeling (SLIM)

- SINBAD - industry supported consortium
- DNOISE - matching from NSERC

Research for 100 % (in)directly funded by industry

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Funding SINBAD II

Funded by *BG, BGP, BP, Chevron, ConocoPhilips, Total SA, Petrobras, PGS, and WesternGeco*

New members: PGS & BGP

DNOISE II: 5-year NSERC CRD awarded Summer '10

- matches *industrial* contributions up to 10 companies
- guarantees *broad* research program centered around *applied* & *theoretical* themes

Drivers

Recent push for FWI calls for

- high-quality *broad-band* data *volumes* (100k channels)
- *larger* offsets & *full* azimuth

Exposes vulnerabilities in our *ability* to control

- *acquisition* costs / time
- *processing* costs / time

Drivers cont'd

Complexity of *inversion* algorithms also *exposes* the "*curse of dimensionality*" in

- **sampling**: *exponential* growth of # *samples* for *high* dimensions
- **optimization**: *exponential* growth of # parameter *combinations* that need to be evaluated to minimize our *objective* functions

Main themes

Make *inversion* less *reliant* on *full* acquisition

Turn *processing* into *inversion* by making *inversion* computationally *feasible* & *robust* with

- *limited* number of *passes* through *all* data and exploiting *fast* matrix-vector *multiplies*
- *randomized*-dimensionality reduction & *sparsity* promotion limiting the data access
- more *forgiving* penalty functionals

What did we set out to do?

What did we set out to do?

Design practical *randomized* acquisition schemes

- performance measures & inclusion prior information

Efficient schemes for *imaging* & *FWI*

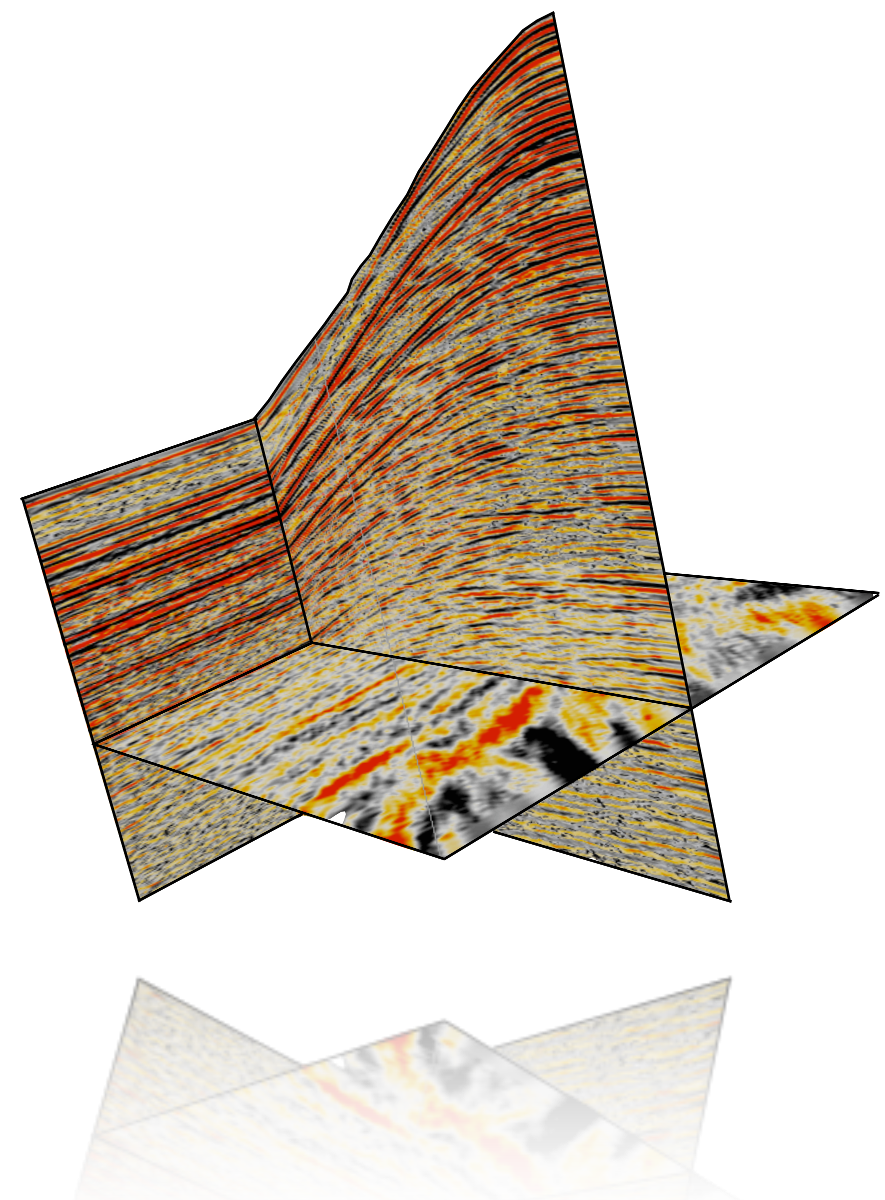
- *randomized* sampling & batching including *extension* of *dimensionality* reduction to marine case

Incorporation of *robustness* in our formulations

- student t & Huber in FWI & sparsity promotion

Improve *uptake* of SLIM's technology by industry

Theme I: Compressive sensing in exploration seismology



Main questions

How can insights from compressive sensing be incorporated into seismic data acquisition?

How can we exploit *structure* exhibited by seismic data?

Can we come up with *quantitative* performance measures predicting the data *quality* after *recovery* from

- (simultaneous) time-compressed *marine* data
- phase-encoded *land* data
- *randomized* superpositions/selections of data

Key strategy

Randomization of acquisition

- *randomized* source/receiver *locations*
- *randomized* time *shifts* in *marine*
- phase encoding on *land* or in *computer*

Turn *coherent* interferences (aliases & source crosstalk) into *Gaussian* “noise”

Use transform-domain (e.g. curvelets) *sparsity* promotion to remove *noisy* crosstalk/interferences...

[Candès et.al, Donoho, '06]

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Sparse recovery

Solve *optimization* problem:

$$\min_{\mathbf{x}} \overbrace{\|\mathbf{x}\|_1}^{\text{detection}} \quad \text{subject to} \quad \overbrace{\mathbf{b} = \mathbf{A}\mathbf{x}}^{\text{data-consistent amplitude recovery}}$$

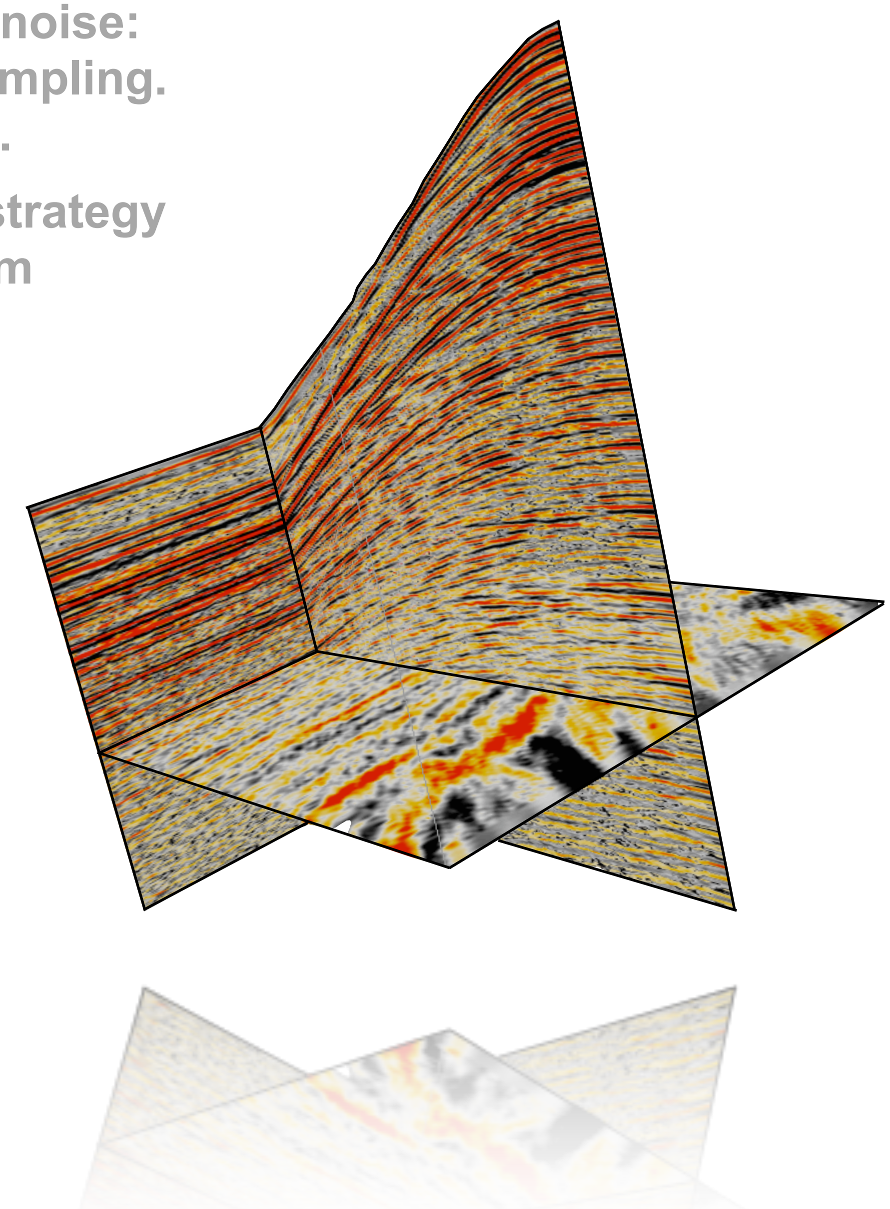
Challenges:

- *design* compressive sensing matrices **A** that *favor* recovery
- large-scale optimization algorithms requiring *few* matvecs

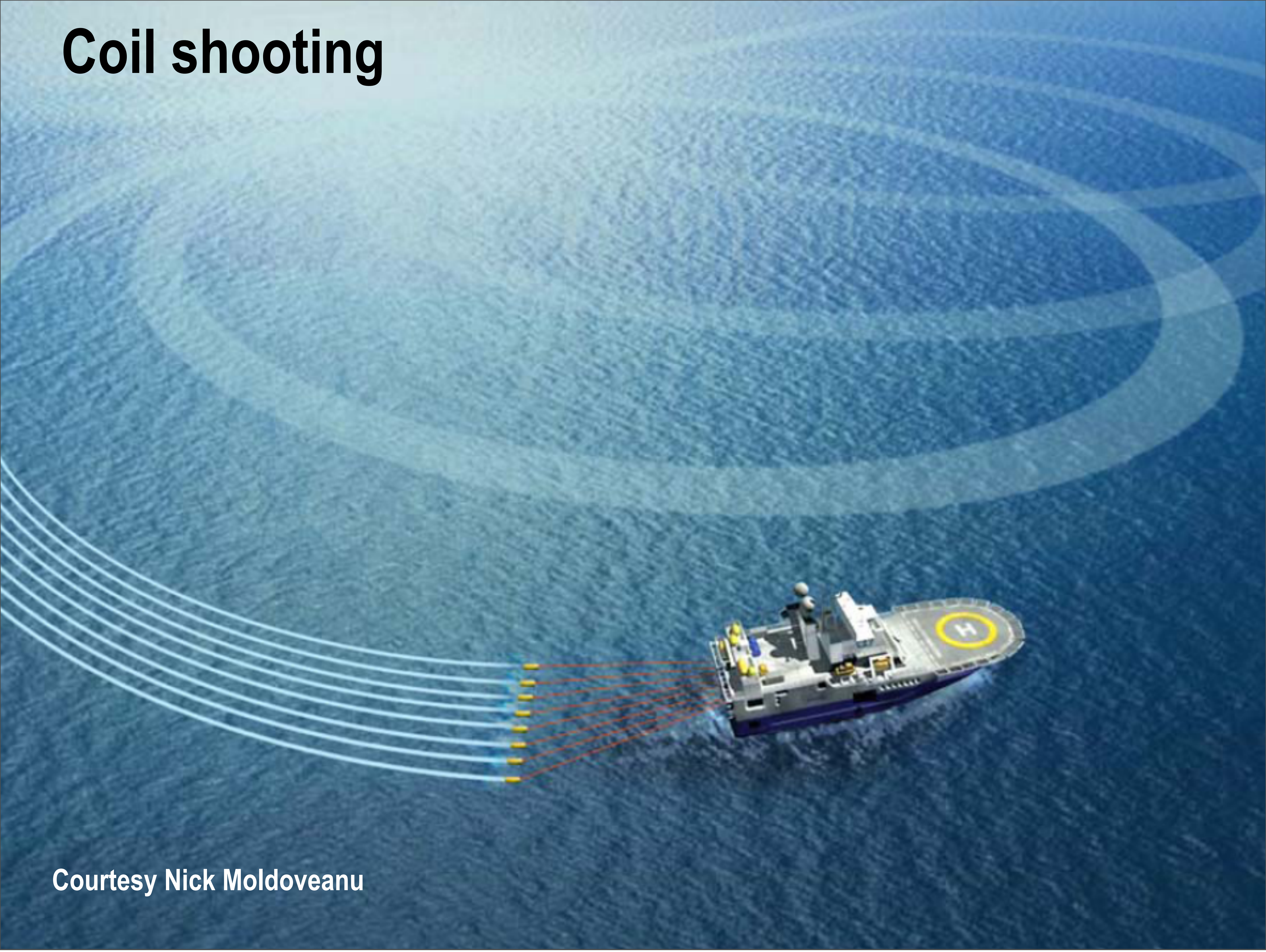
Randomized coil sampling

Hennenfent, G. and Herrmann, F. J. Simply denoise: wavefield reconstruction via jittered under-sampling. Geophysics, Vol. 73, No. 3, pp. V19–V28, 2008.

Nick Moldoveanu. Random sampling: A new strategy for marine acquisition. SEG Technical Program Expanded Abstracts, 29(1):51–55, 2010.



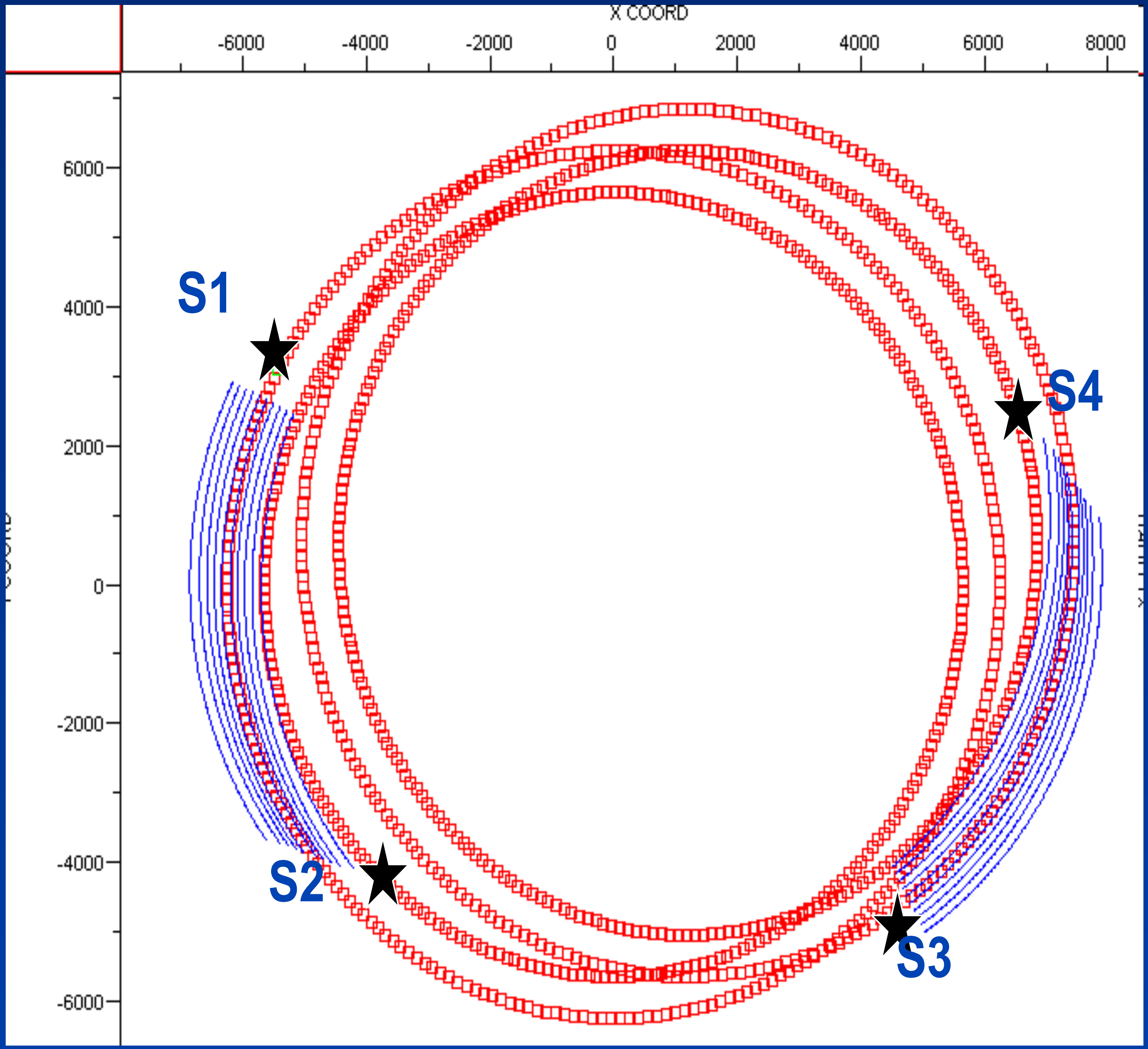
Coil shooting



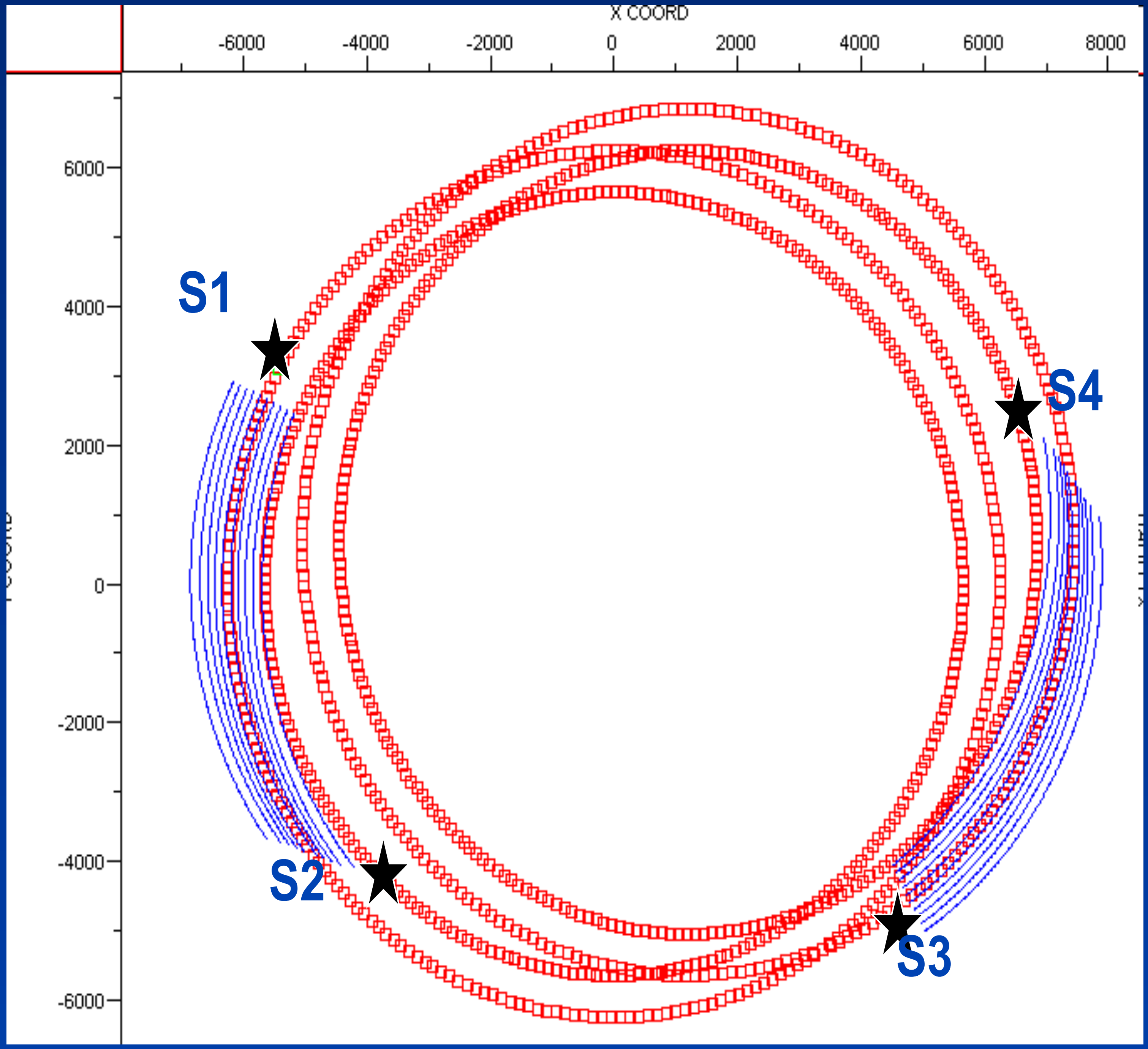
Courtesy Nick Moldoveanu

Multivessel coil shooting

Multivessel coil shooting



Multivessel coil shooting



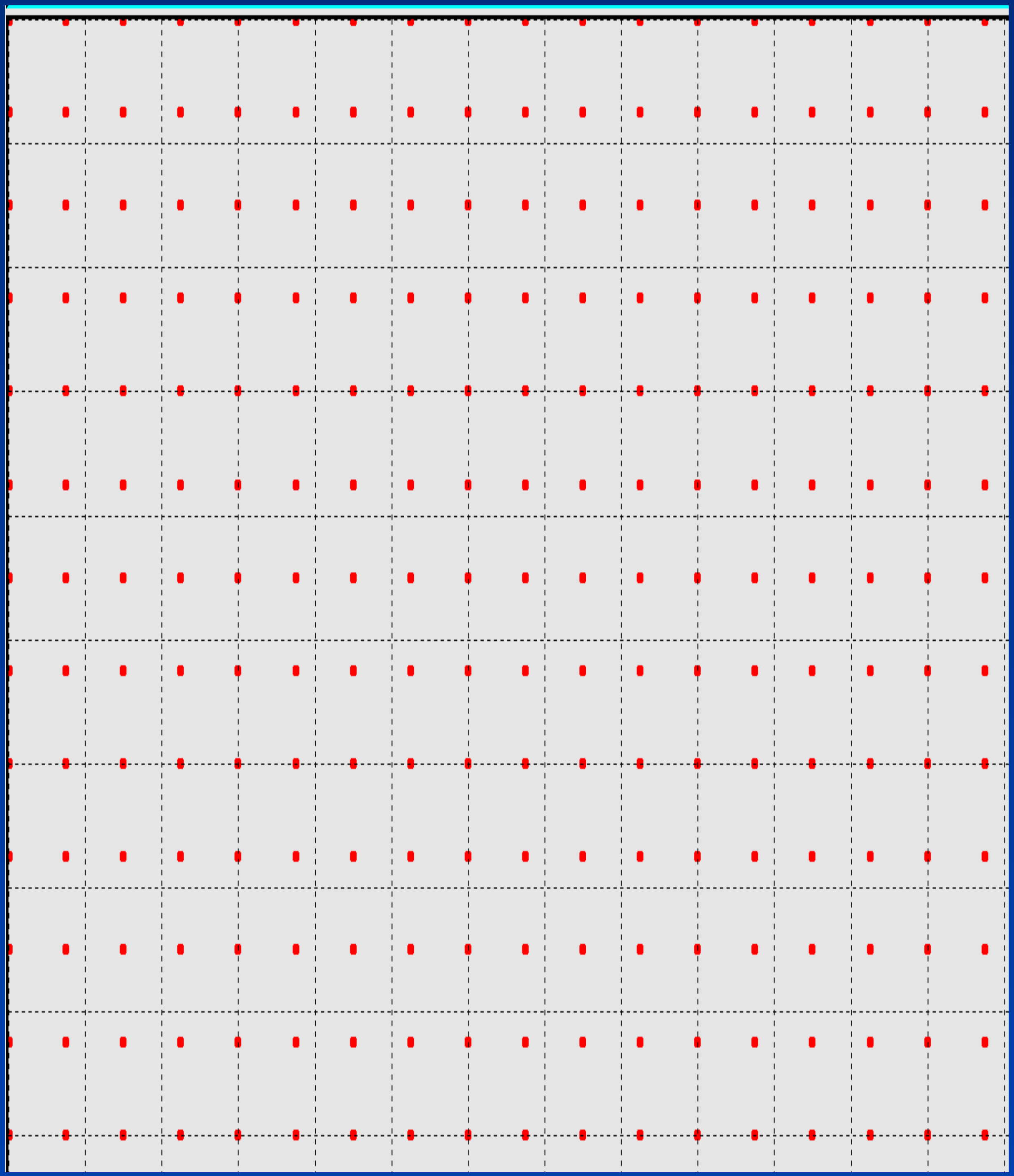
$$W(t, x_s, y_s, x_r, y_r)$$

Coil center grid design

Courtesy Nick Moldoveanu

Coil center grid design

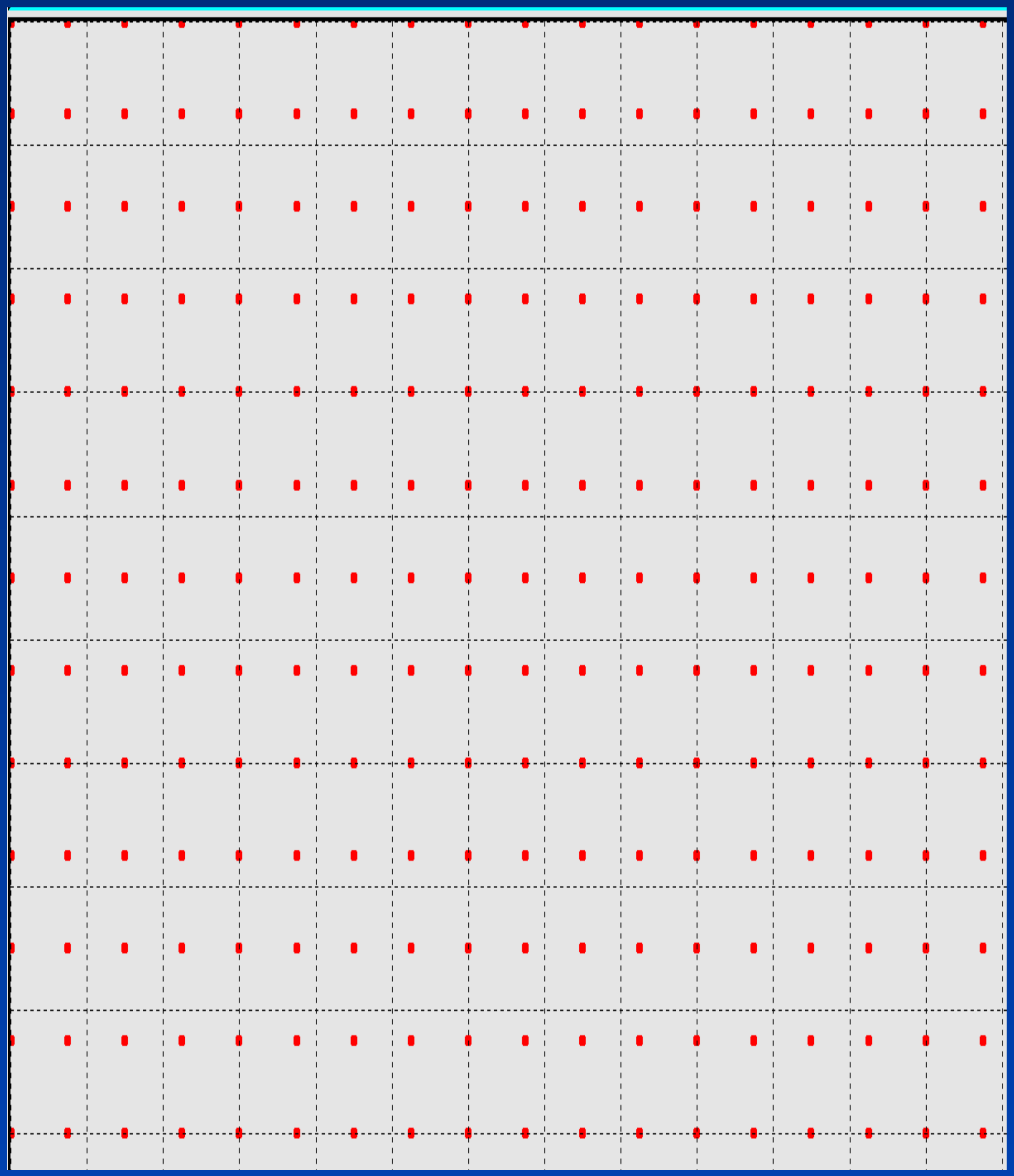
Regular center distribution



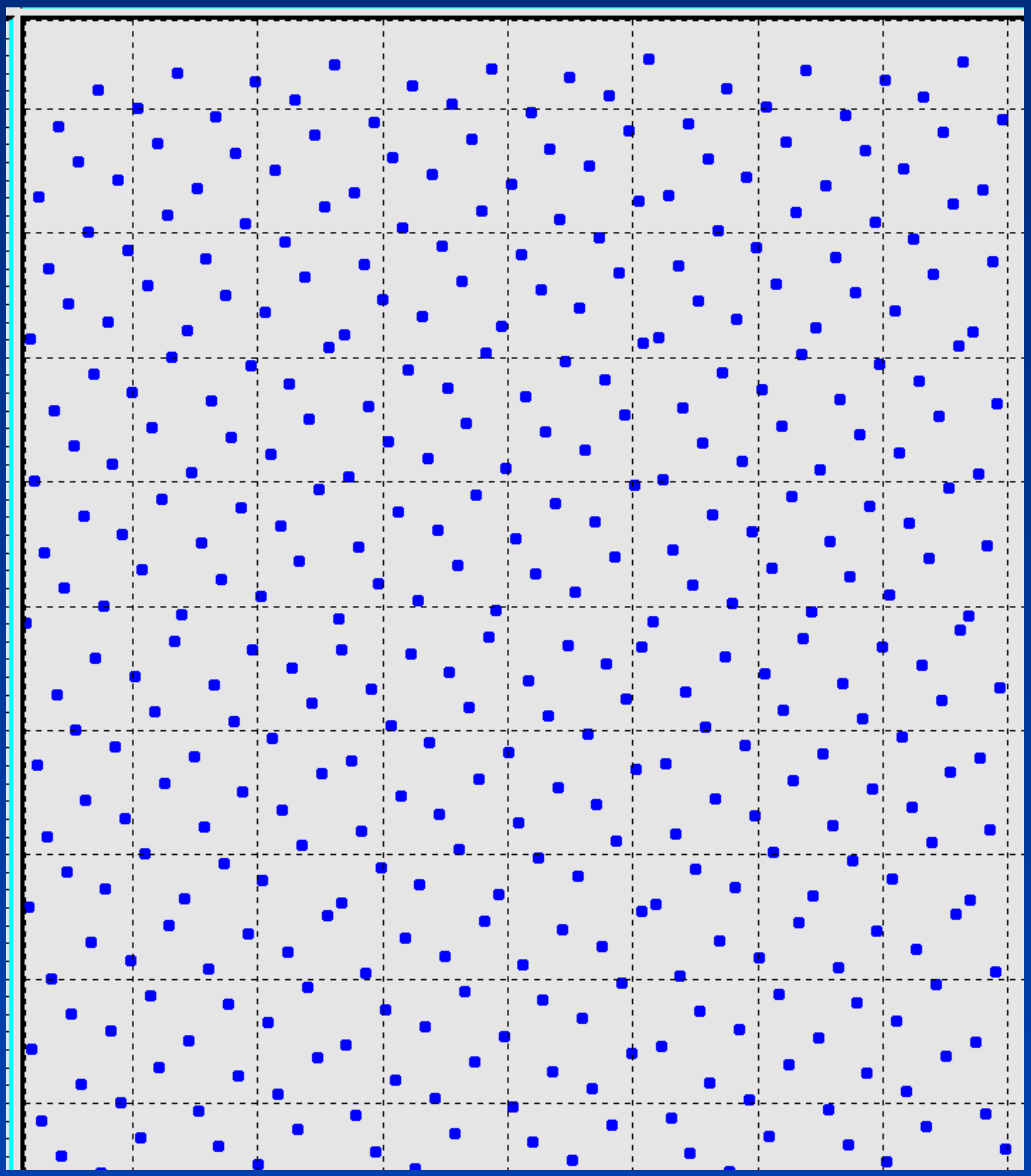
Courtesy Nick Moldoveanu

Coil center grid design

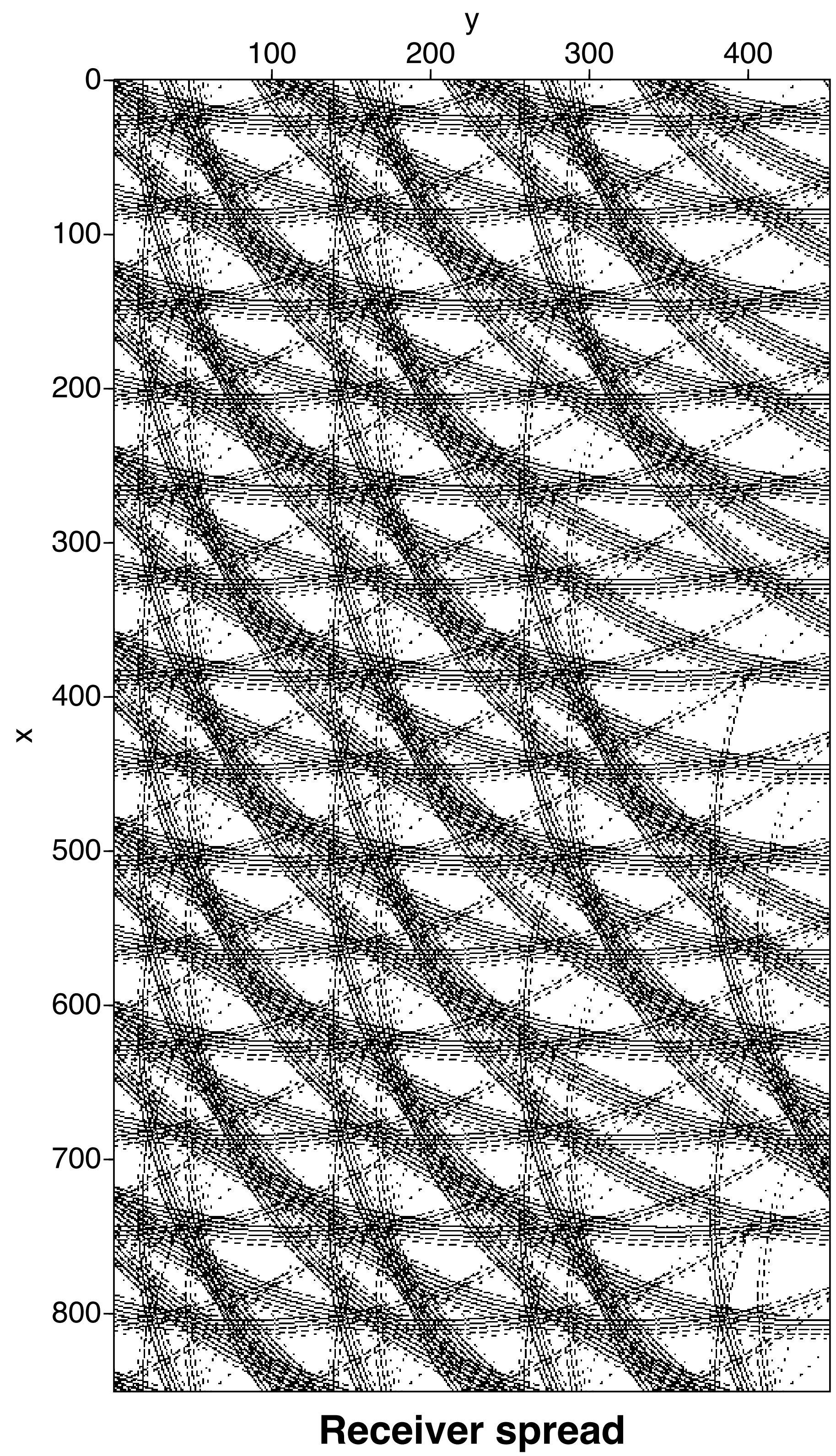
Regular center distribution



Random center distribution

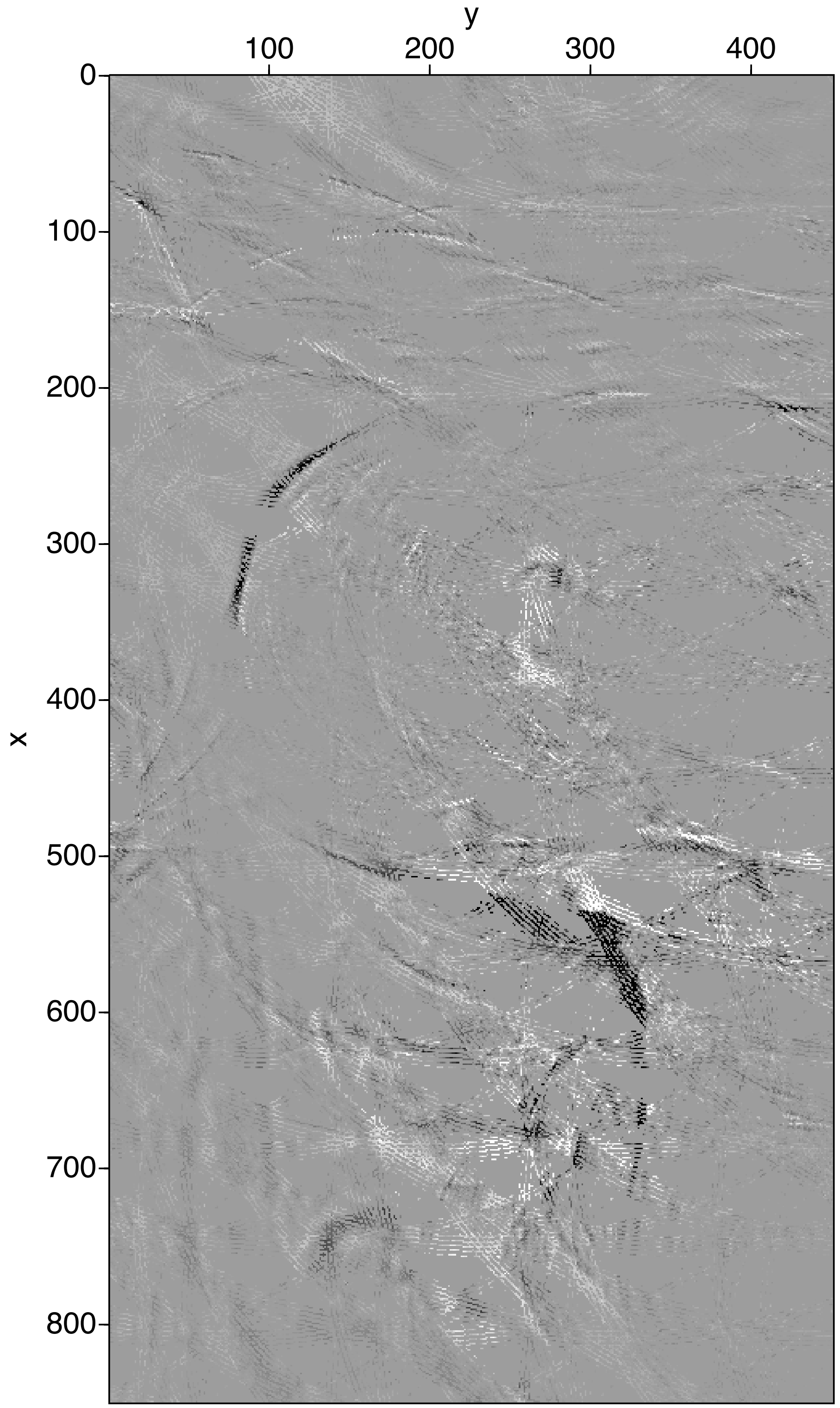


Courtesy Nick Moldoveanu

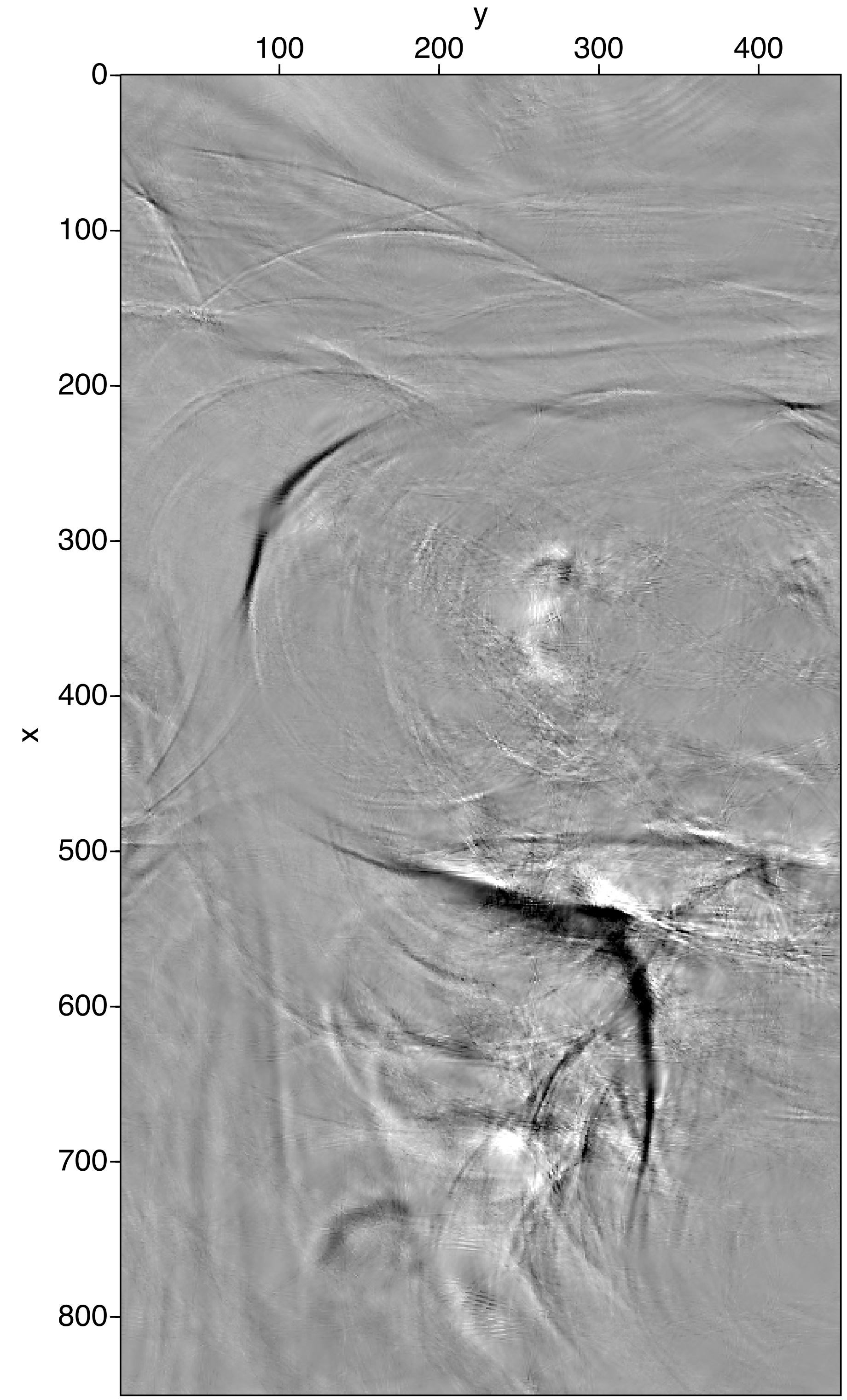


34 % of samples

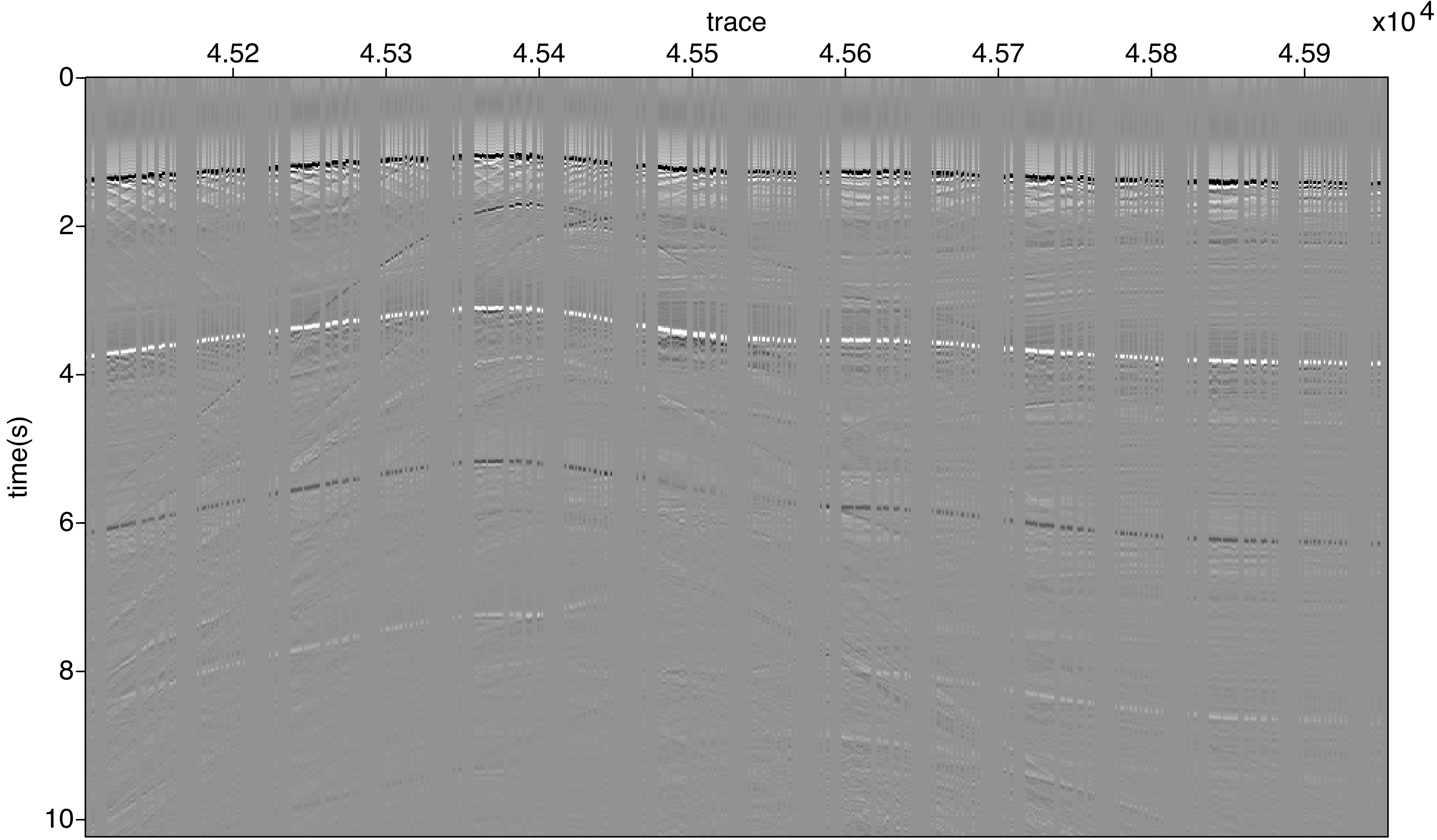
Courtesy Nick Moldoveanu



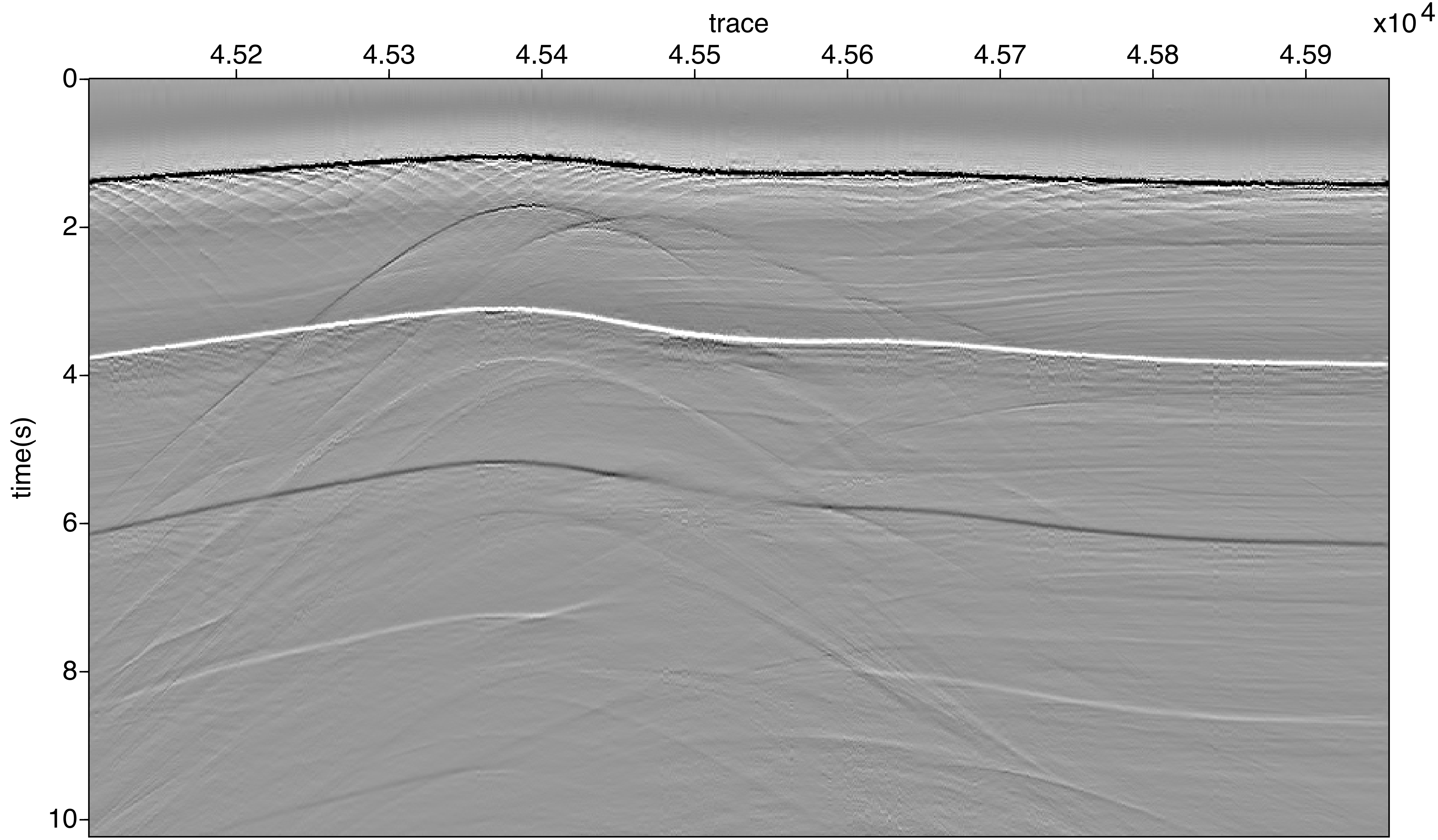
Input data



Interpolation with 2D Curvelet



Input data



Interpolation with 2D Curvelet

Observations

```
Starting SPGl1 recovery...

 ================================================================================
 SPGL1_SLIM v. 46  (Tue, 14 Jun 2011) based on v.1017
 ================================================================================
 No. rows               : 103672320      No. columns           : 1459253760
 Initial tau            : 0.00e+00      Two-norm of b         : 3.92e+05
 Optimality tol         : 1.00e-04      Target objective      : 0.00e+00
 Basis pursuit tol      : 1.00e-06      Maximum iterations    :      110

  Iter      Objective   Relative Gap  Rel Error      gNorm   stepG   nnzX    nnzG            tau
     0  3.9236638e+05  0.0000000e+00   1.00e+00  6.903e+03     0.0       0       0  2.2303101e+07
     1  3.9219958e+05  1.9364118e+00   1.00e+00  6.677e+03    -0.3       2       0
     2  3.4192692e+05  2.1884194e+00   1.00e+00  5.147e+03     0.0   14452       0
     3  3.2859582e+05  4.1722491e-01   1.00e+00  1.373e+03     0.0   48295       0

   108  1.5609476e+03  1.6347854e+04   1.00e+00  7.335e+00     0.0  356264726      0
   109  1.5850938e+03  9.3198454e+04   1.00e+00  4.283e+01     0.0  346355398      0
   110  1.5641524e+03  6.9308202e+04   1.00e+00  3.104e+01     0.0  345144021      0

 ERROR EXIT -- Too many iterations

 Products with A      :     125        Total time   (secs) :  34838.7
 Products with A'     :     112        Project time (secs) :  2875.2
 Newton iterations    :      26        Mat-vec time (secs) :  25882.1
 Line search its      :      23        Subspace iterations :      0
```

Observations

Sparse recovery gives *encouraging* results

Able to *scale* sparse recovery to "large" problem sizes

Sparsity-promoting program *far* from reaching *convergence*

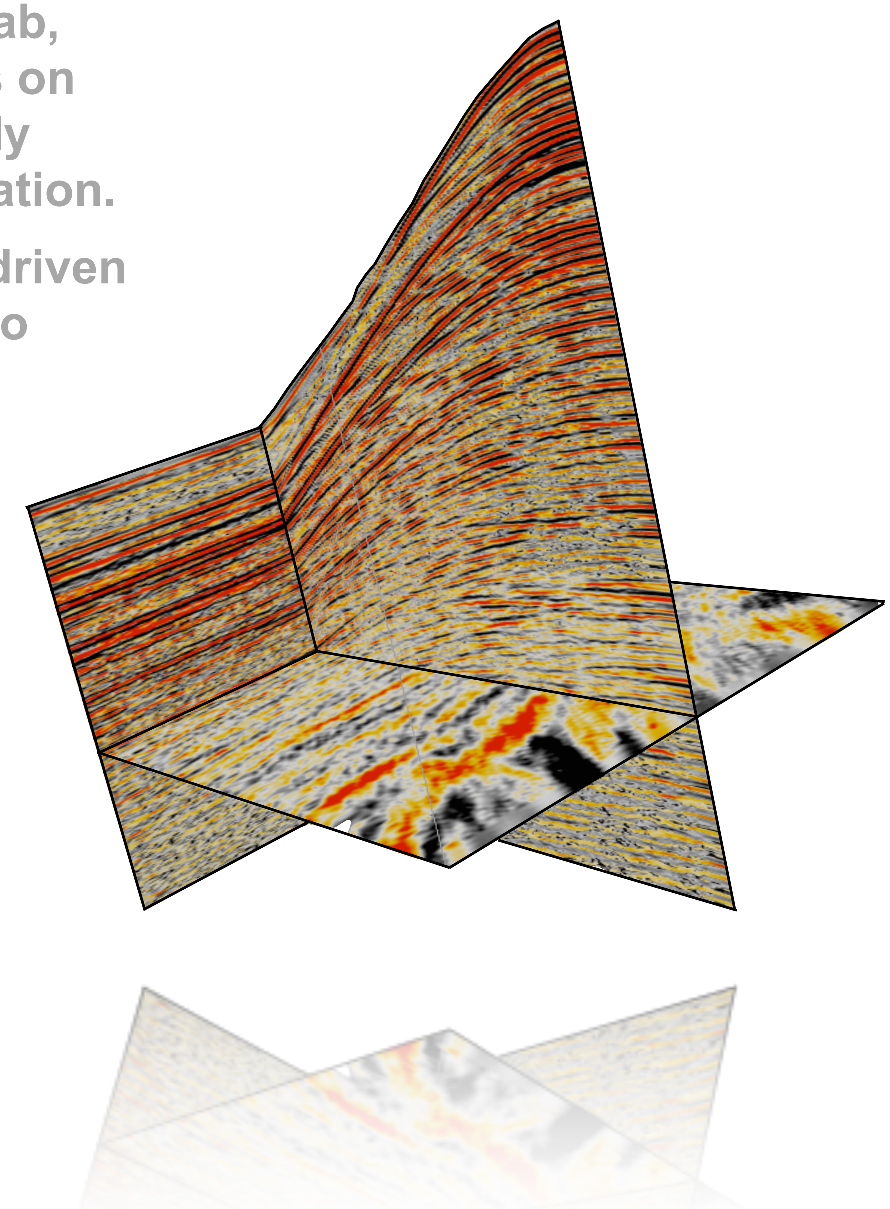
- what are *good* criteria to *measure* performance
- how can we *improve* convergence & *scale*

Explore *similarities* in *supports* of *neighboring* offsets & azimuth...

Compressed sensing with *prior* information

M. P. Friedlander, Hassan Mansour, Rayan Saab, Ozgur Yilmaz. To appear in IEEE Transactions on Information Theory. Recovering compressively sampled signals using partial support information.

Hassan Mansour and Ozgur Yilmaz. Support driven reweighted ℓ_1 minimization. Submitted to ICASSP 2012, 9/27/2011.



Key contributions

Use *support* information in *sparse* recovery

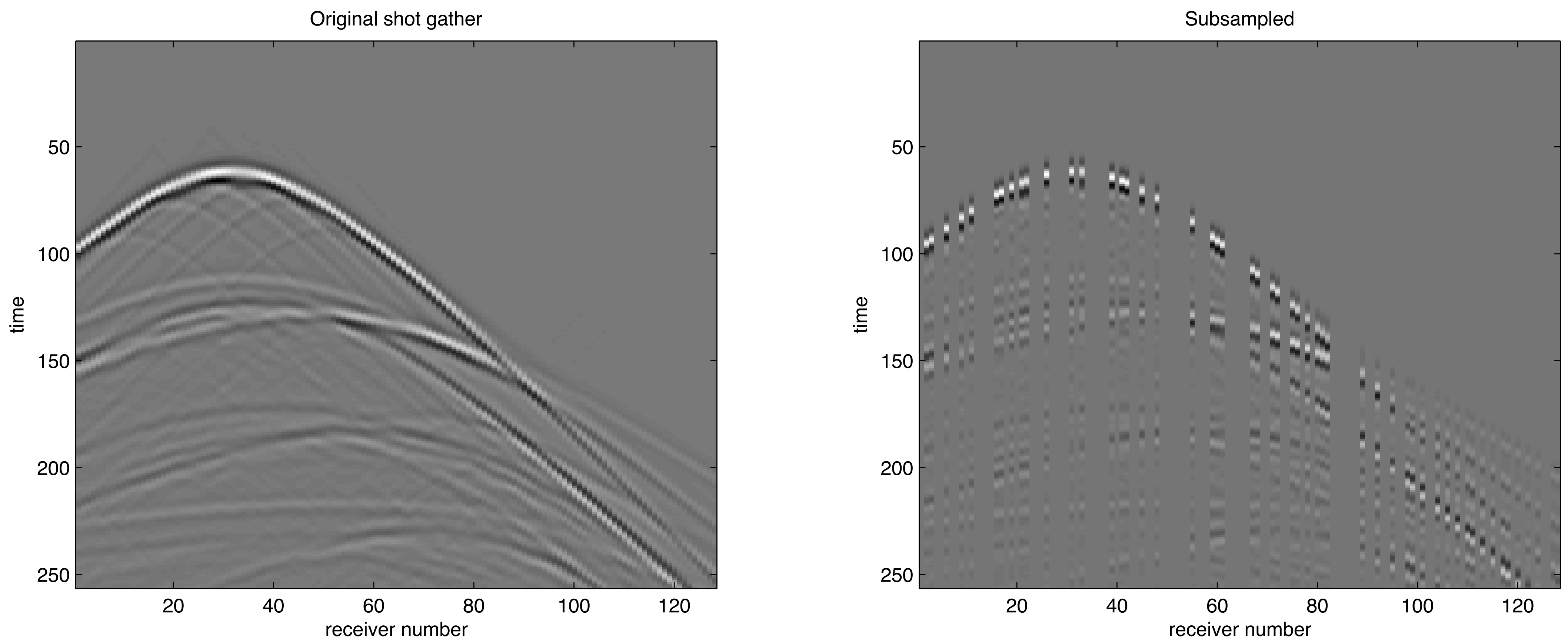
Involves *prior* knowledge on the *support* from

- other seismic data or physics (minimal velocity)
- *neighboring* azimuth/offset (smoothness along wavefronts & reflectors)

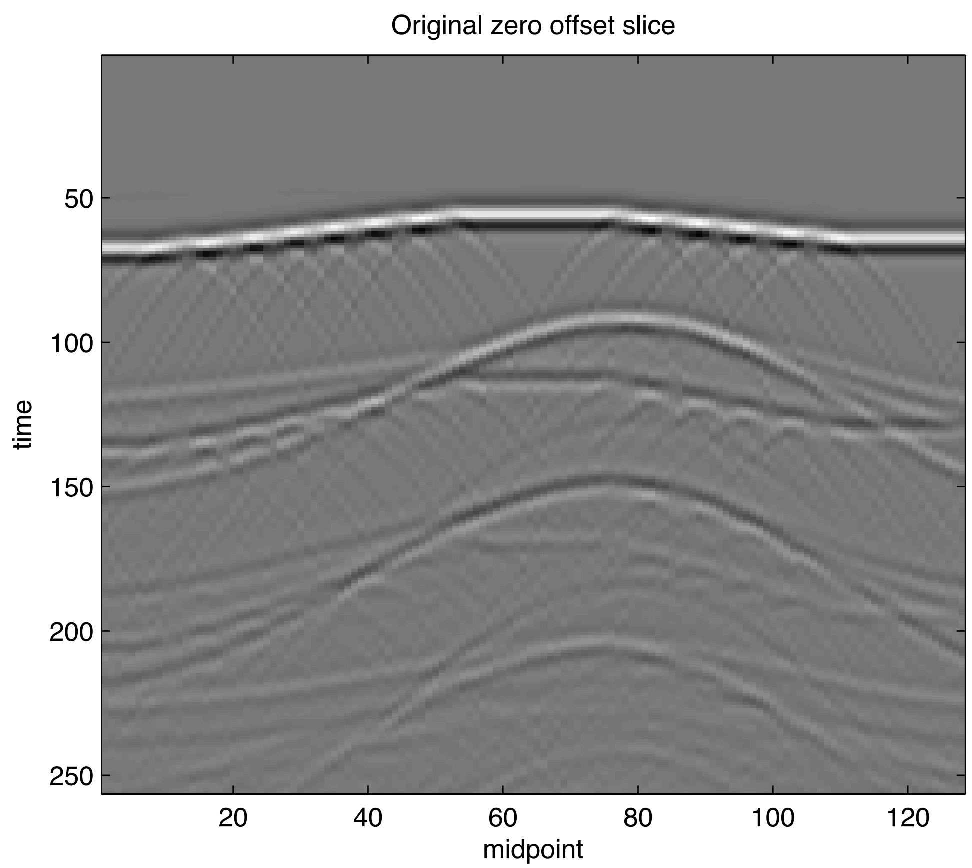
Opportunity:

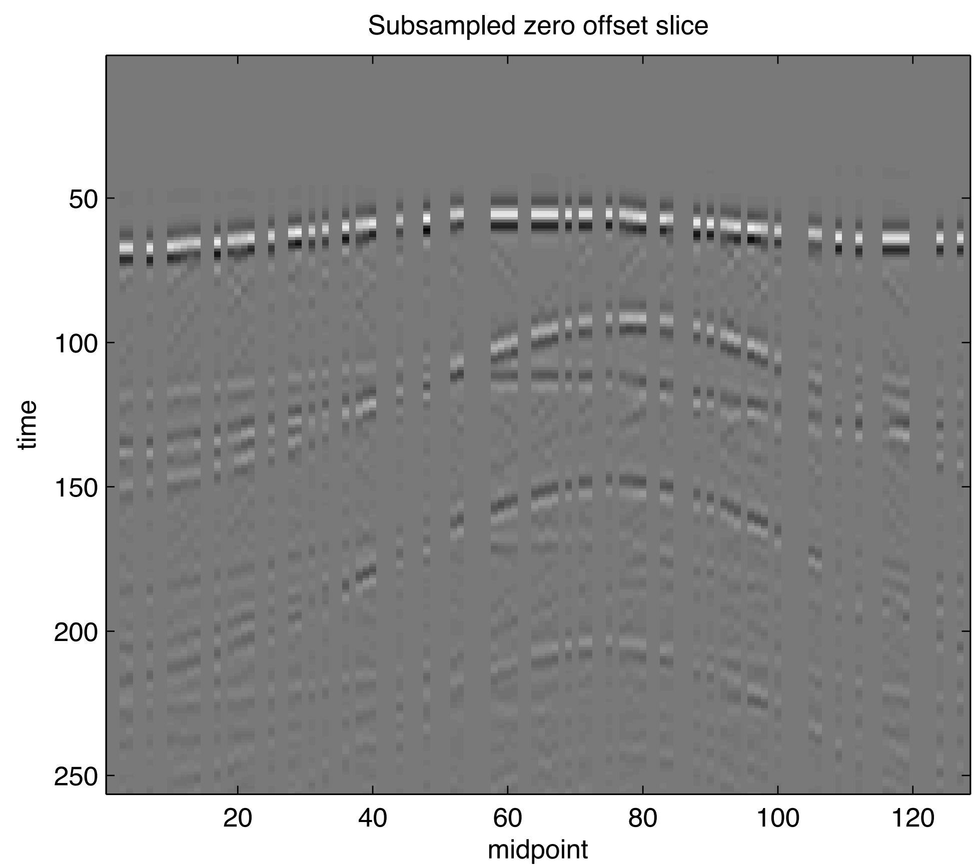
- *improved* recovery & opportunity to design new CS matrices/acquisitions

Random subsampling

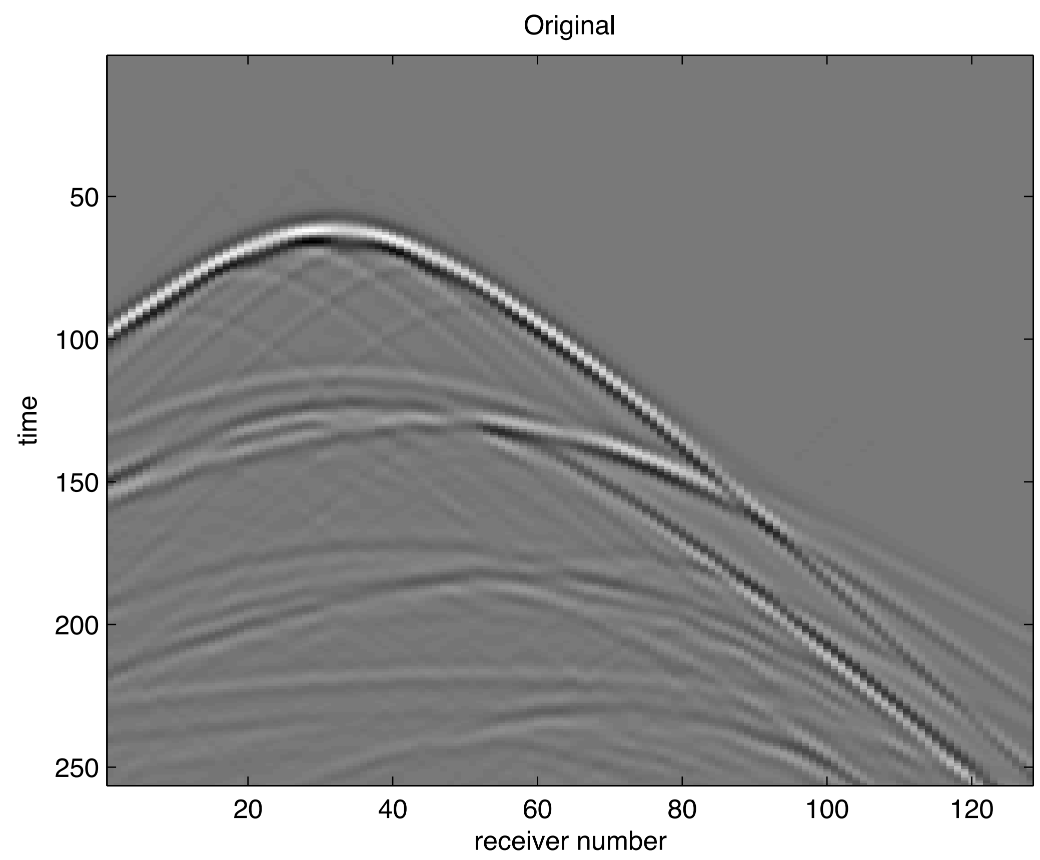


Random subsampling

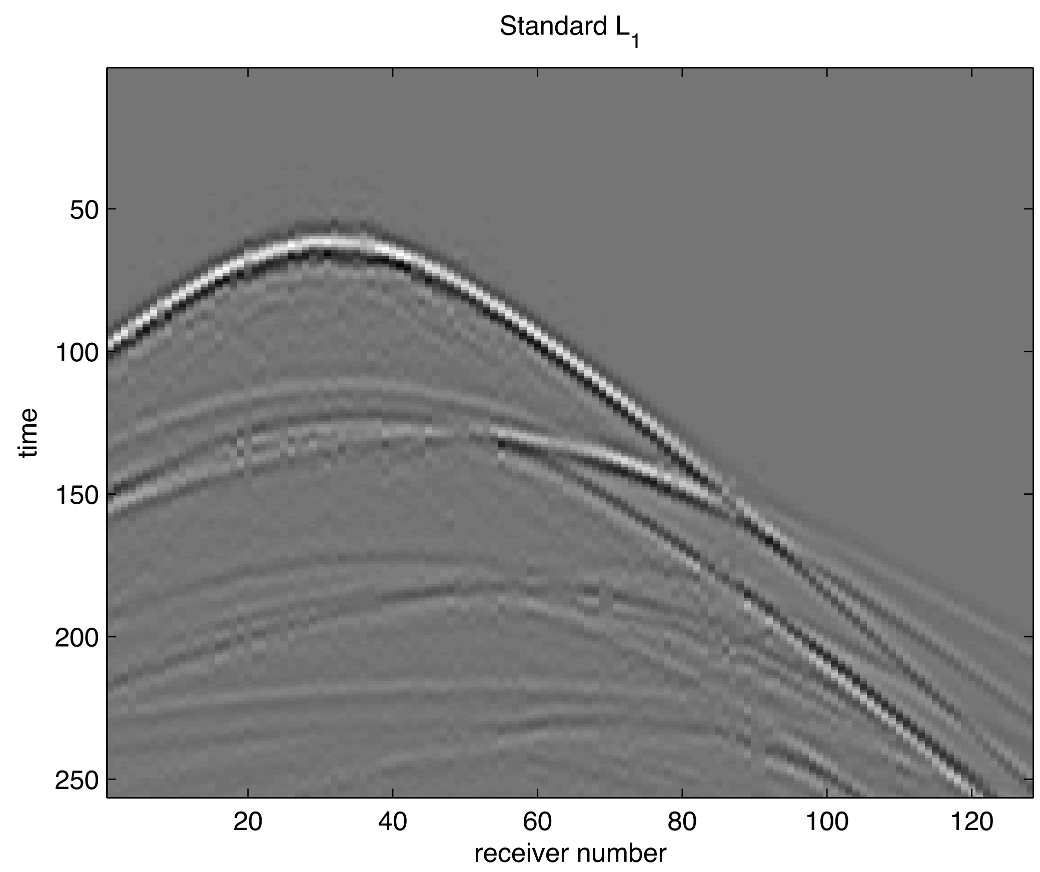




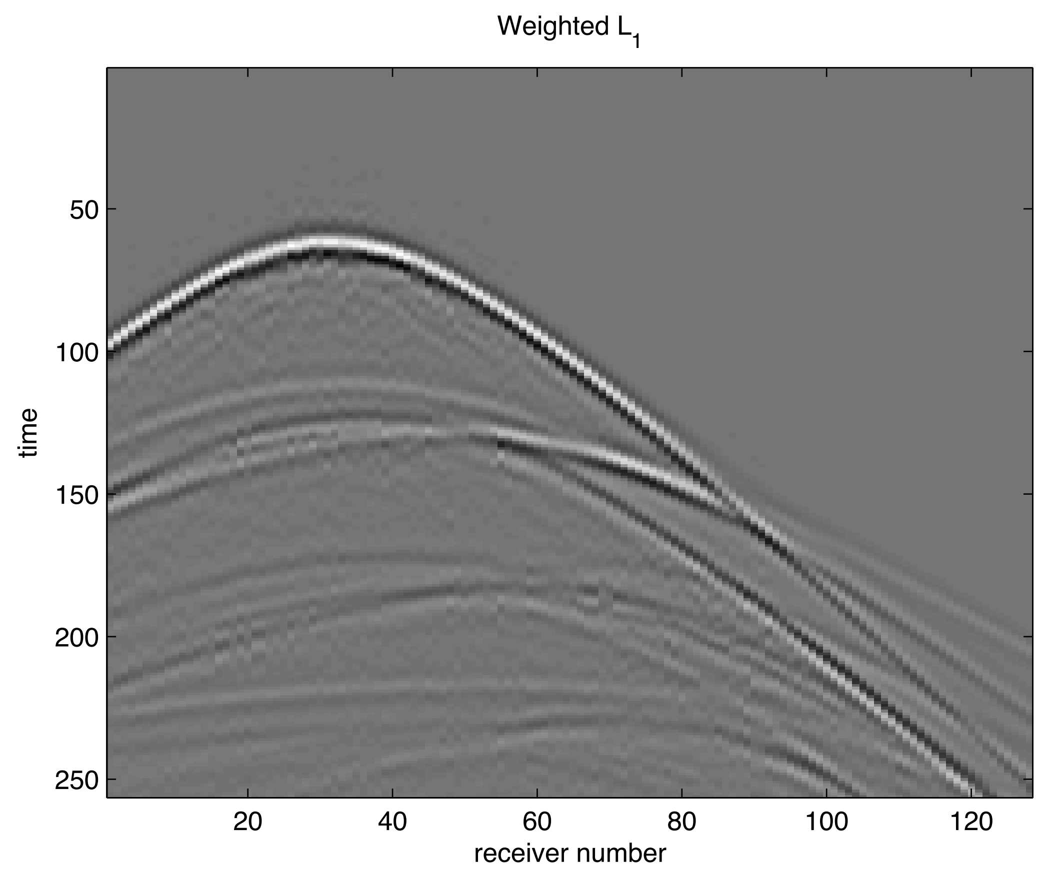
Shot record #30



Standard L1

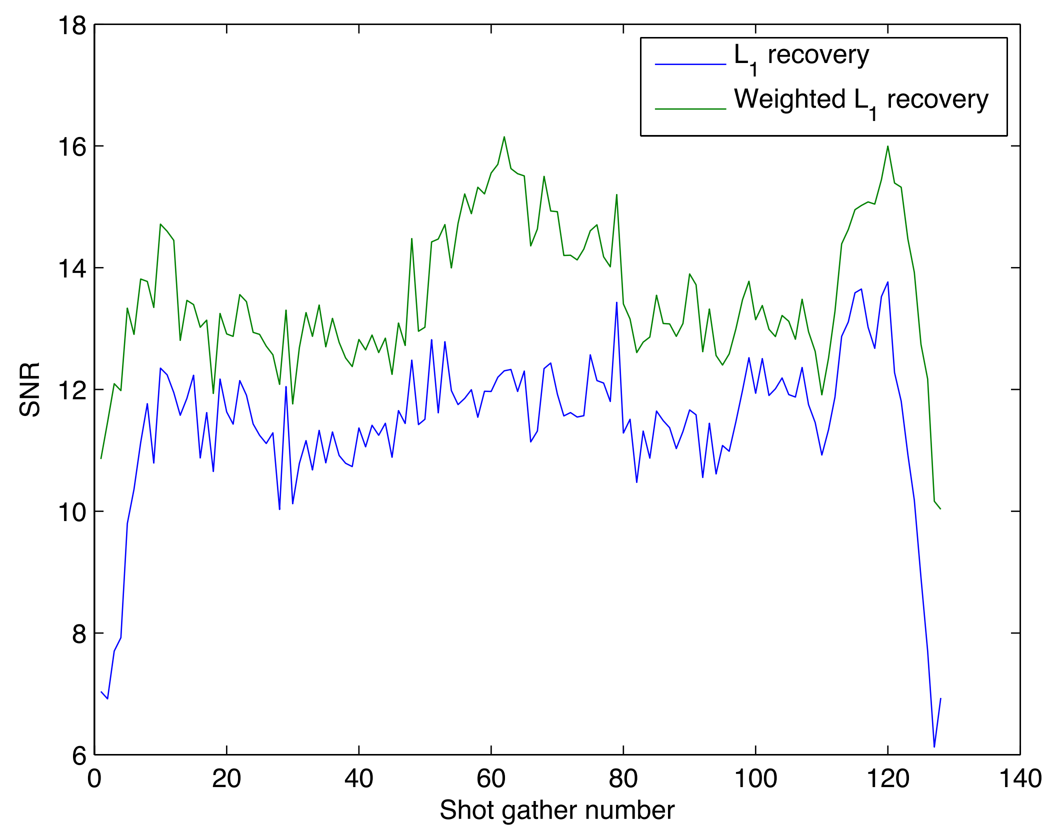

Standard L_1
time
50
100
150
200
250
20
40
60
80
100
120
receiver number

Weighted L1



Weighted L_1
time
50
100
150
200
250
20
40
60
80
100
120
receiver number

SNR comparison

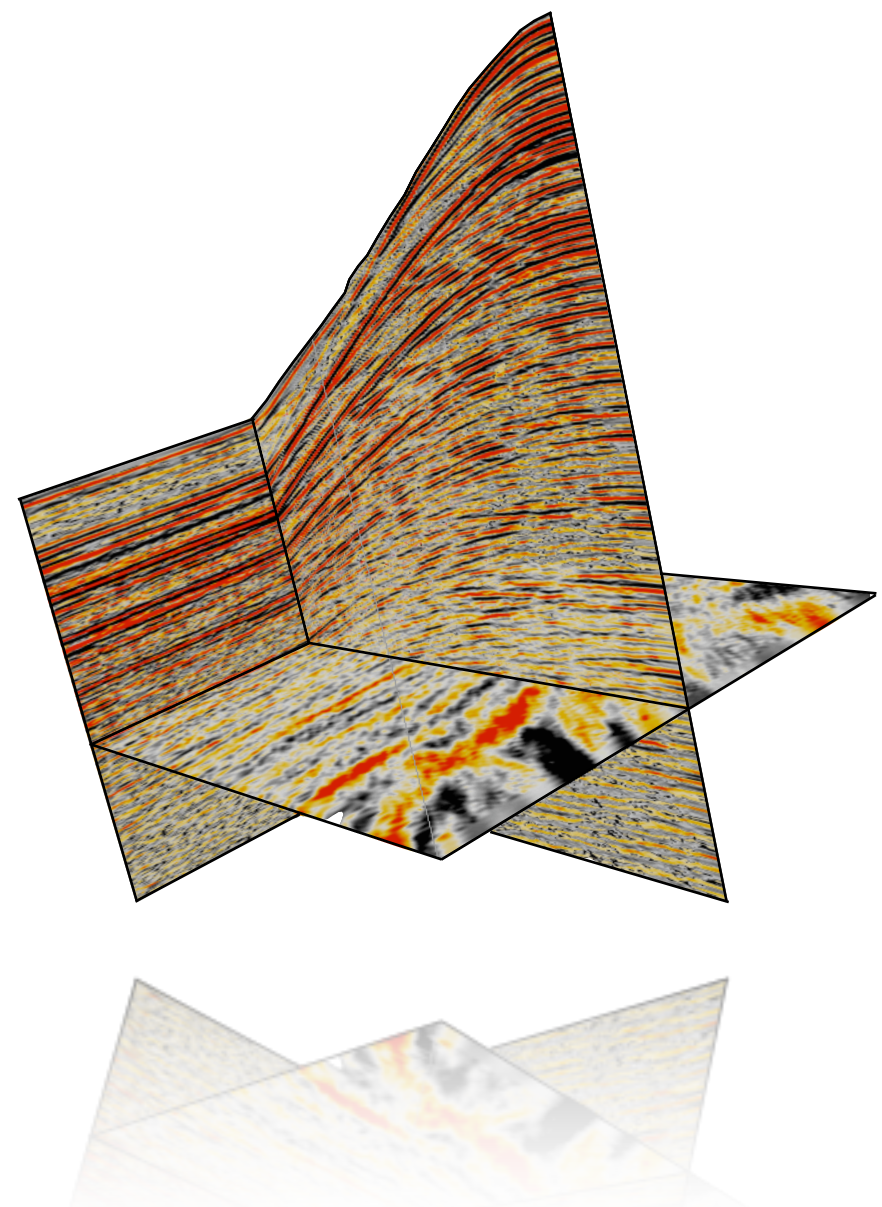


Only dither: efficient marine acquisition "without" sim. sourcing & why do curvelets work?

Hassan Mansour, Haneet Wason, Tim T.Y. Lin, and Felix J. Herrmann. TR-2011-04. Simultaneous-source marine acquisition with compressive sampling matrices. In revision.

Hassan Mansour, Haneet Wason, Tim T.Y. Lin, and Felix J. Herrmann. TR-2011-04r. Randomized marine acquisition “without” simultaneous sourcing

Haneet Wason, Felix J. Herrmann, and Tim T.Y. Lin. Sparsity-promoting recovery from simultaneous data: a compressive sensing approach. SEG 2011, San Antonio.



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Key contributions

Quantitative analysis of *marine* acquisition with CS

- requires *prior* knowledge on the *support* (nonzeros)
- subject to *physical* constraints
- involves *extremely* large matrices

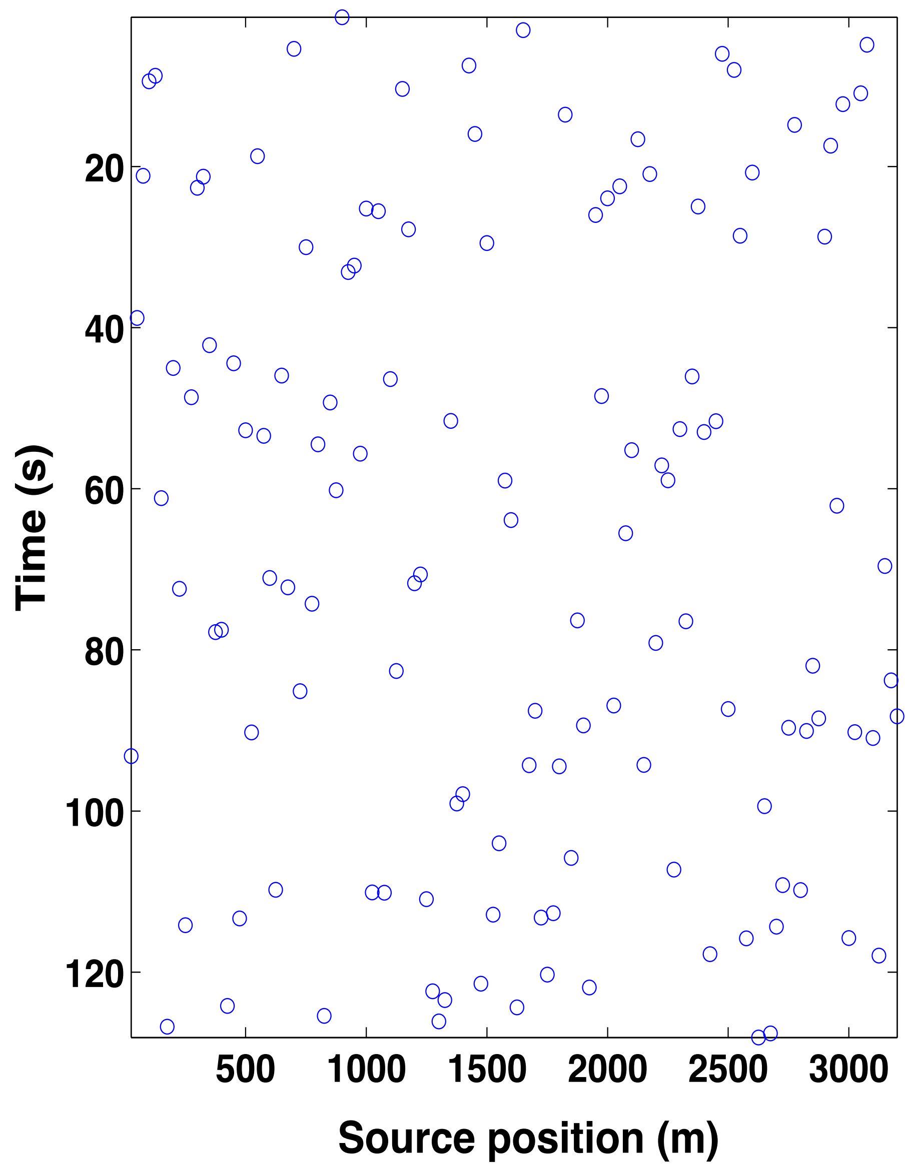
Relying on time *dithering* only.

Opportunities & challenges

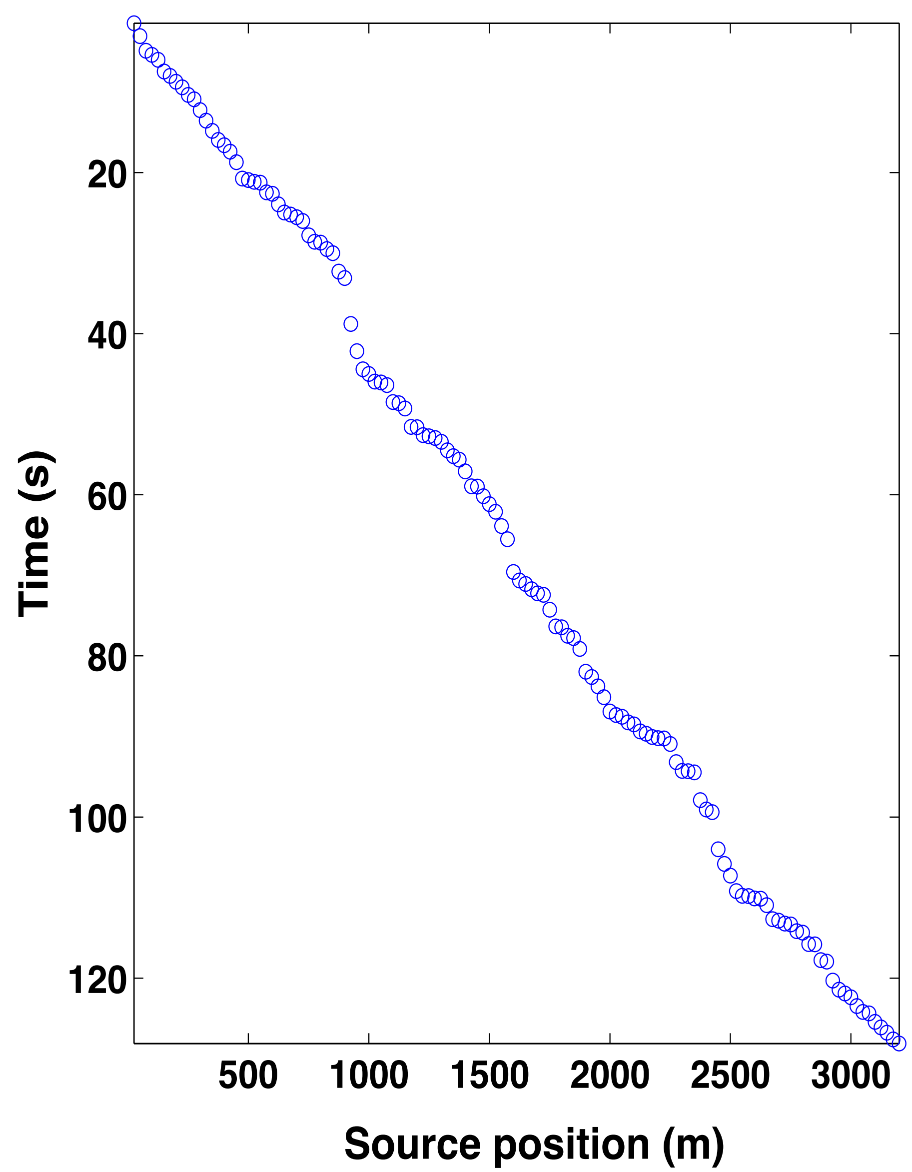
- *marine* acquisition with *few simul*taneous sources possibly in *combination* with OBC/OB-nodes

Simultaneous acquisition sampling schemes

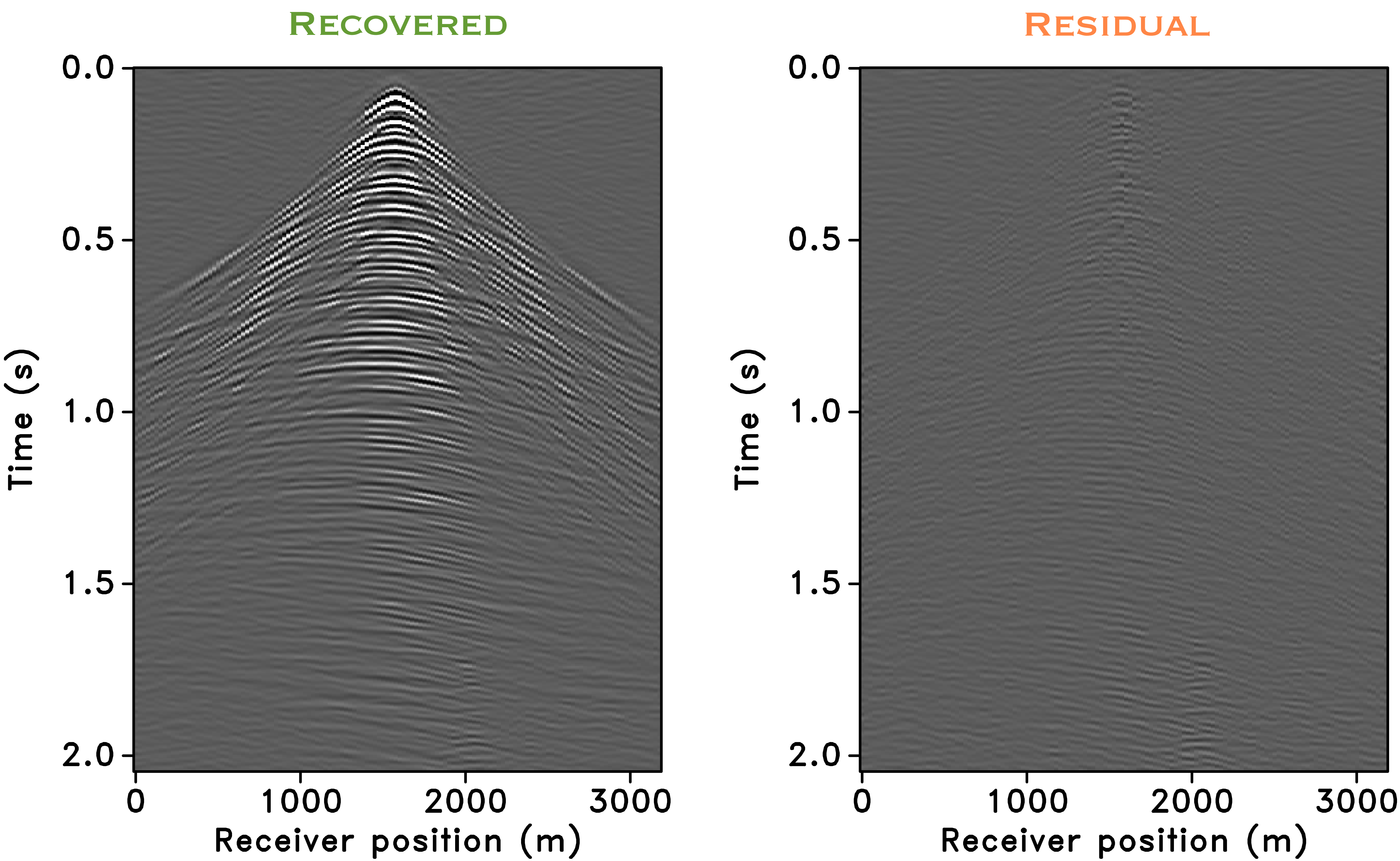
"Ideal" simultaneous acquisition



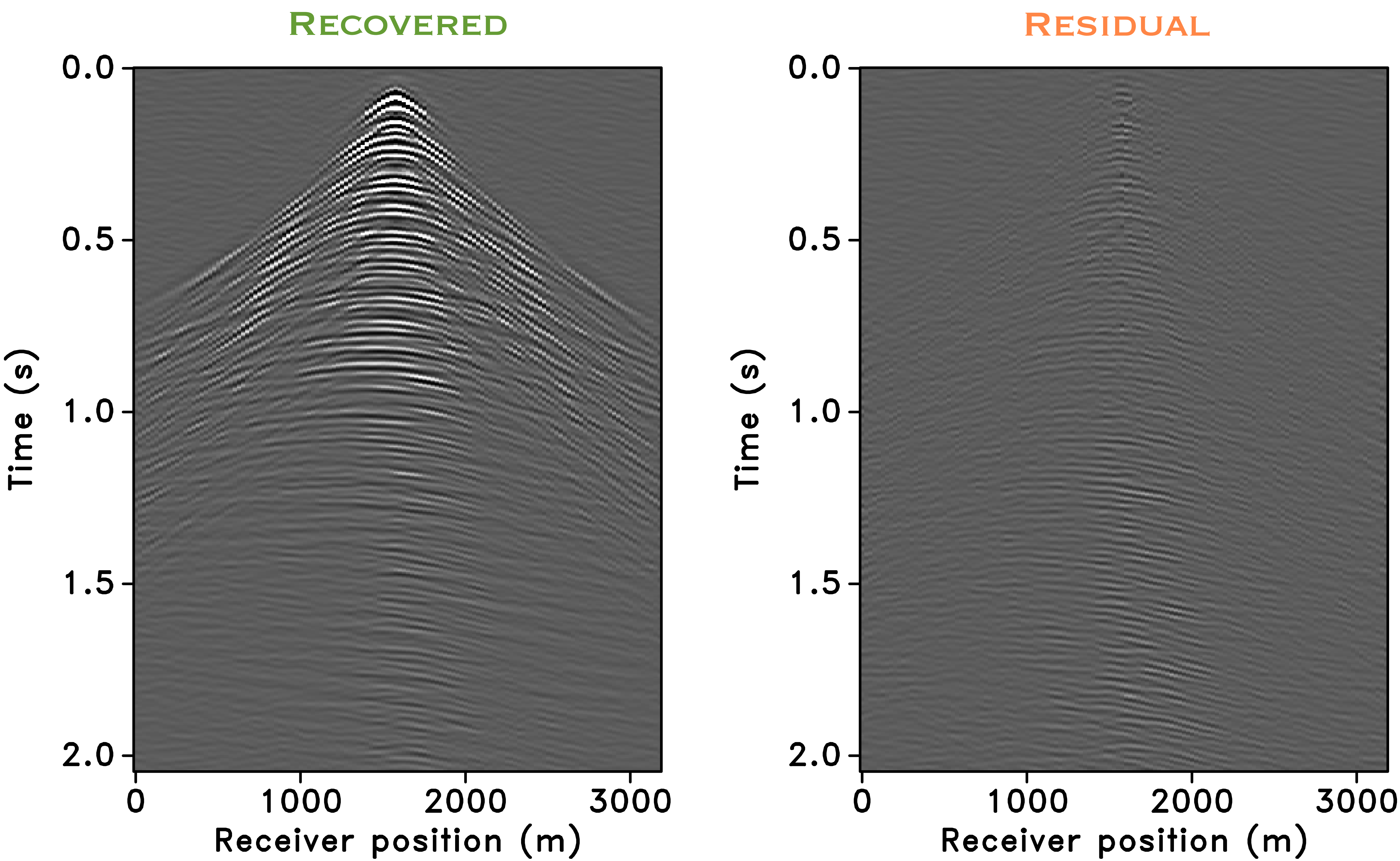
Random time-dithering



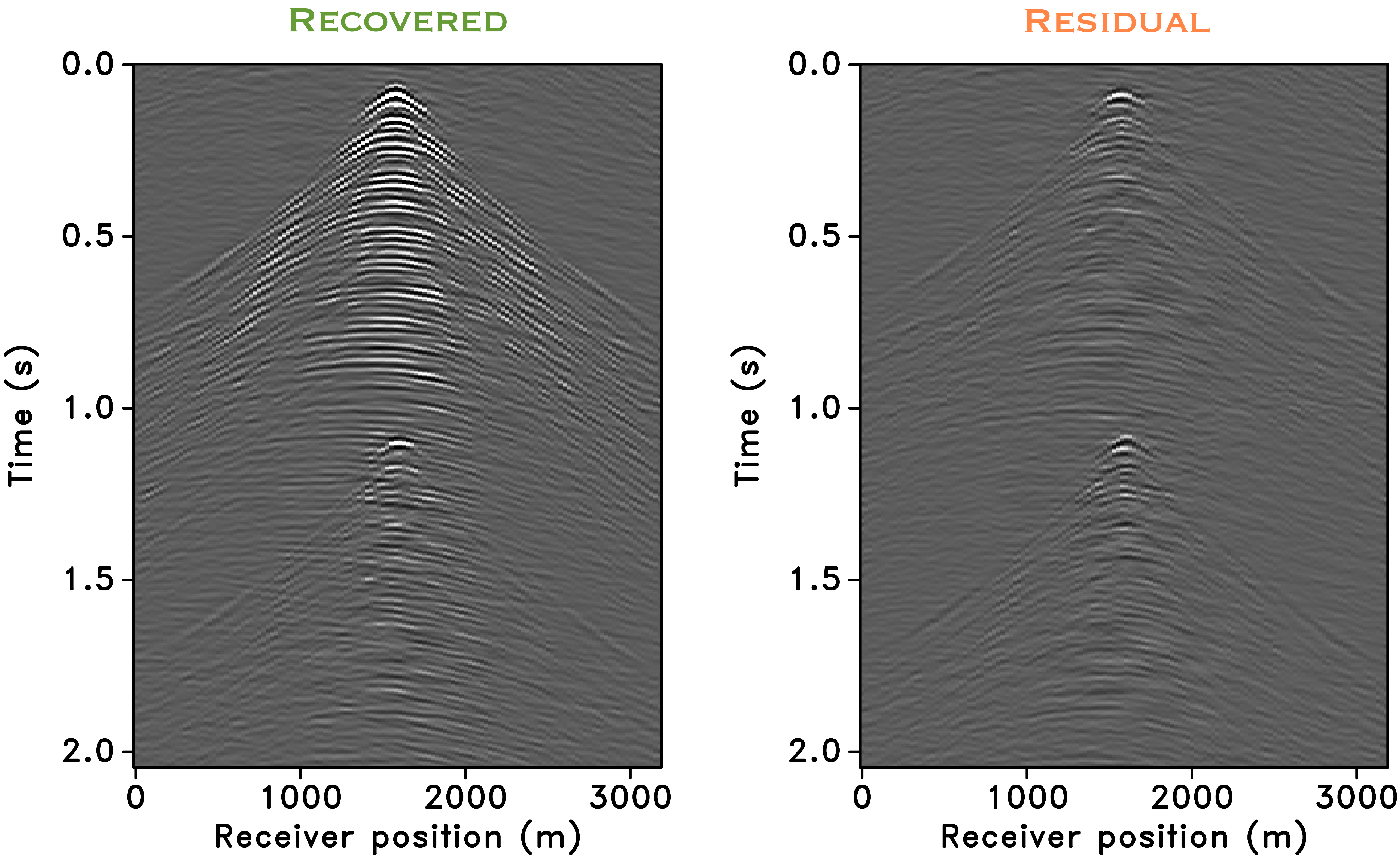
Random dithering (sparsity-promoting recovery)
SNR = 10.5 dB



Random time-shifting (sparsity-promoting recovery)
SNR = 8.06 dB



Constant time-shifting (sparsity-promoting recovery)
SNR = 4.80 dB



Outcomes

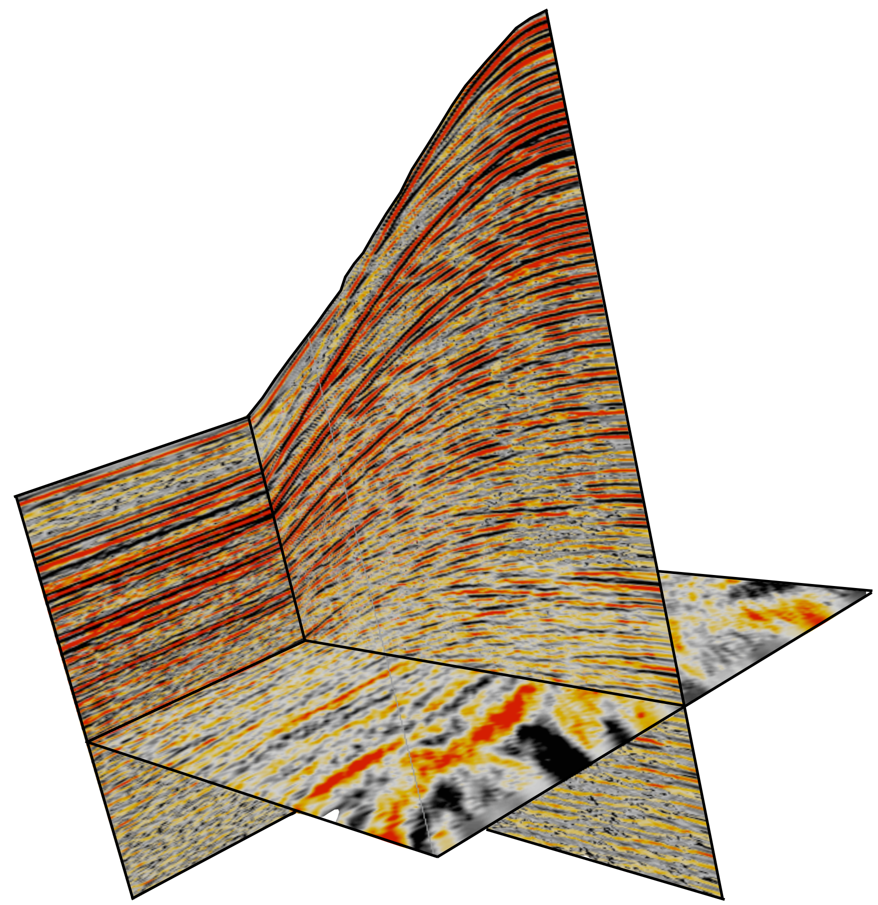
Uptake by industry

- coil sampling by WesternGeco
- *field* studies by *several* oil companies incorporating our ideas in *land* and *marine* acquisition

More information from *fewer* data by *adapting* insights from compressive sensing

- quantitative performance measures remain illusive
- *scale to 3D is challenging*

Theme II: Free-surface and overburden mitigation



Main questions

How can we use *physics* of the free *surface/overburden* to our *advantage*?

How can we exploit *image* space *sparsity*?

How can we manage *storage* and *computational* demands of *data*-driven methods involving *dense* matrices?

How can we use *multiple*-reflected wavefields in *imaging*?

Key strategy

Leverage physics combined with *sparsity* promotion exploiting

- relationships between *up*- and *down-going* wavefields
- *redundant* multiple *energy*
- *data* & *image* domain *sparsity*

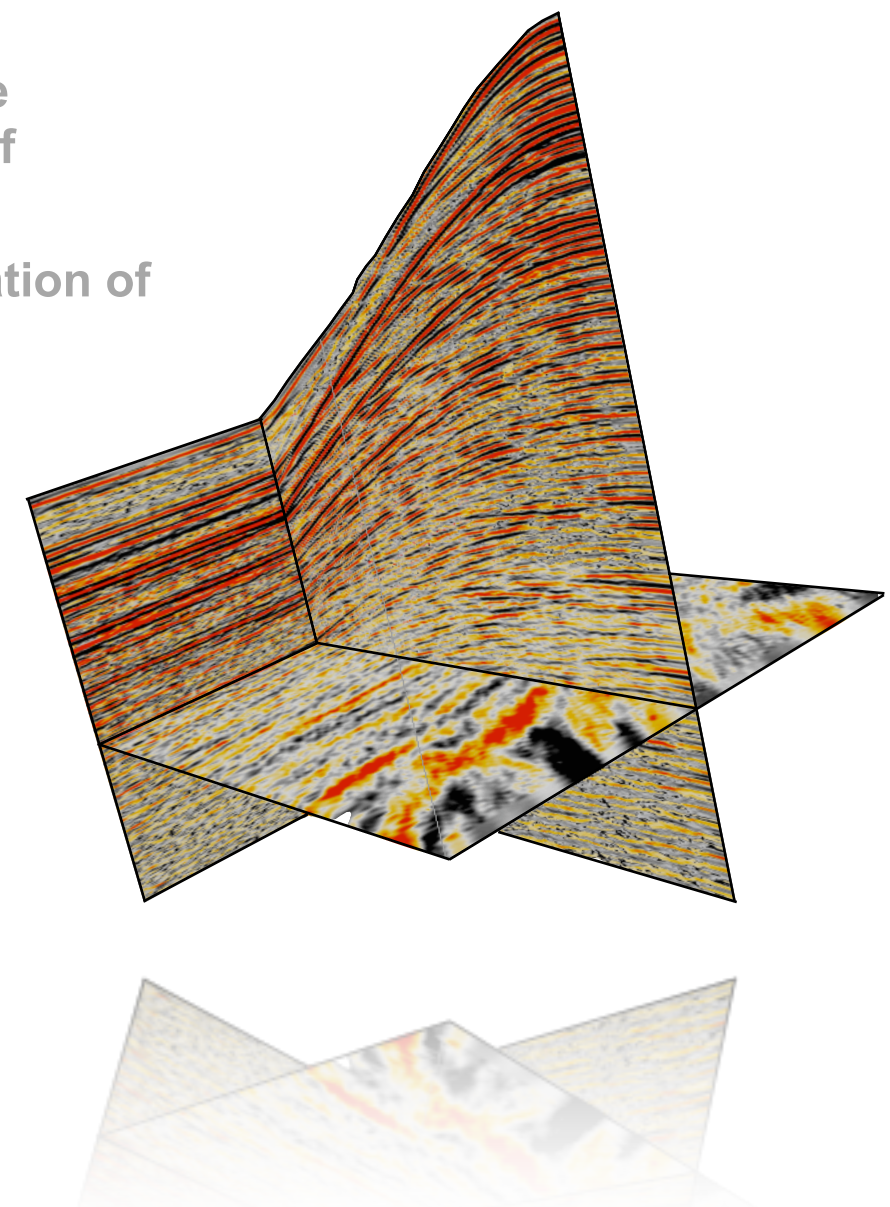
Turn *coherent* noise into coherent (imaged) *events*.

Use (bi)convex structure to promote *sparsity* and to add *robustness* to ‘incoherent‘ *noise*.

Inside the Robust EPSI formulation

Tim Lin and Felix J. Herrmann. Robust source signature deconvolution and the estimation of primaries by sparse inversion. SEG 2011.

Tim Lin and Felix J. Herrmann. Robust estimation of primaries by sparse inversion. In preparation.



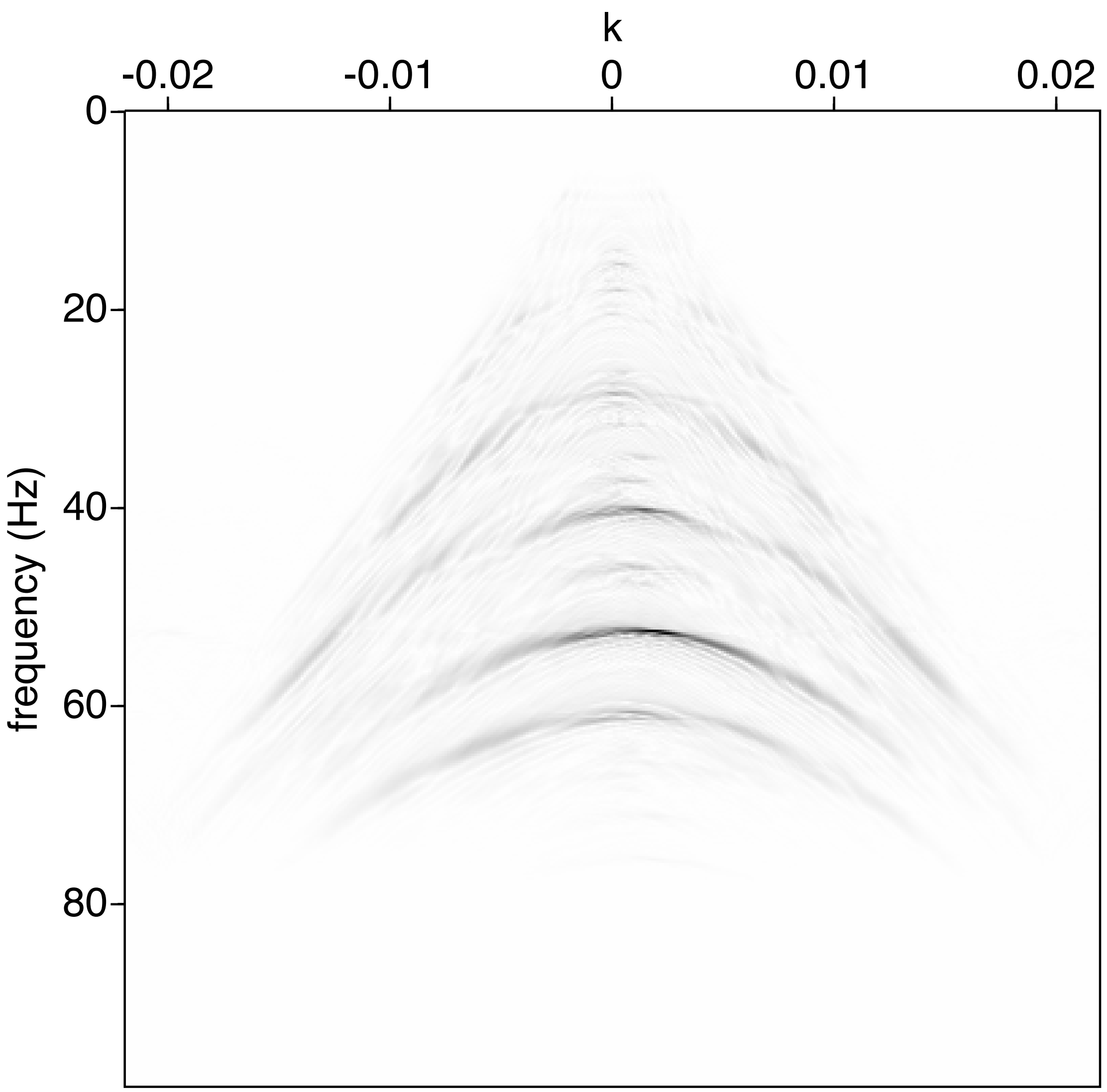
Key contributions

Robust formulation of EPSI

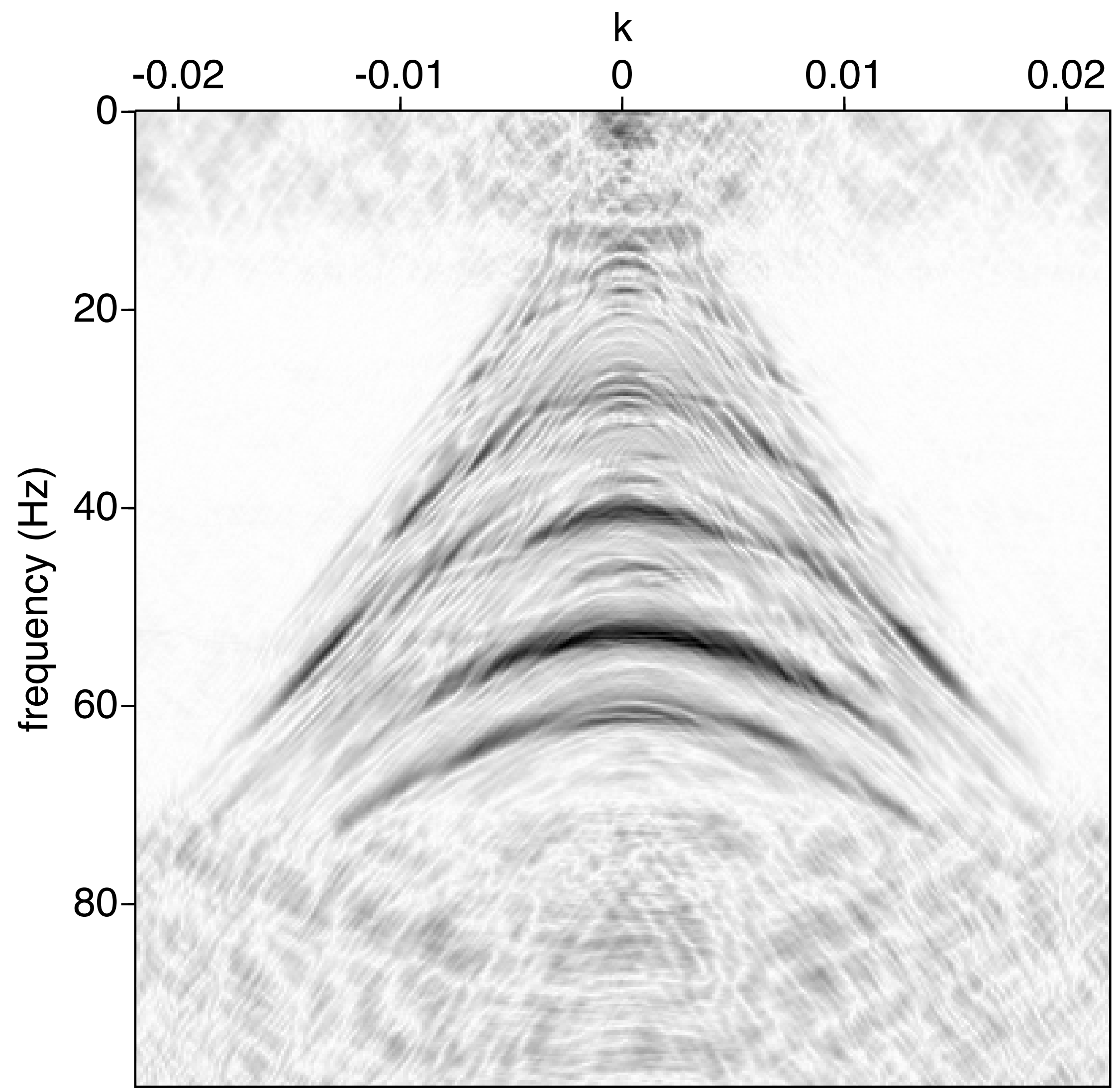
- exploits *bi-convex* (one-norm) and *sparse* (curvelets) structure to estimate *Green's* function and *source*
- *resolves* delicate *scaling* issues with proper *linesearch*
- does *not* require *extensive* parameter *selection*

Opportunities & challenges

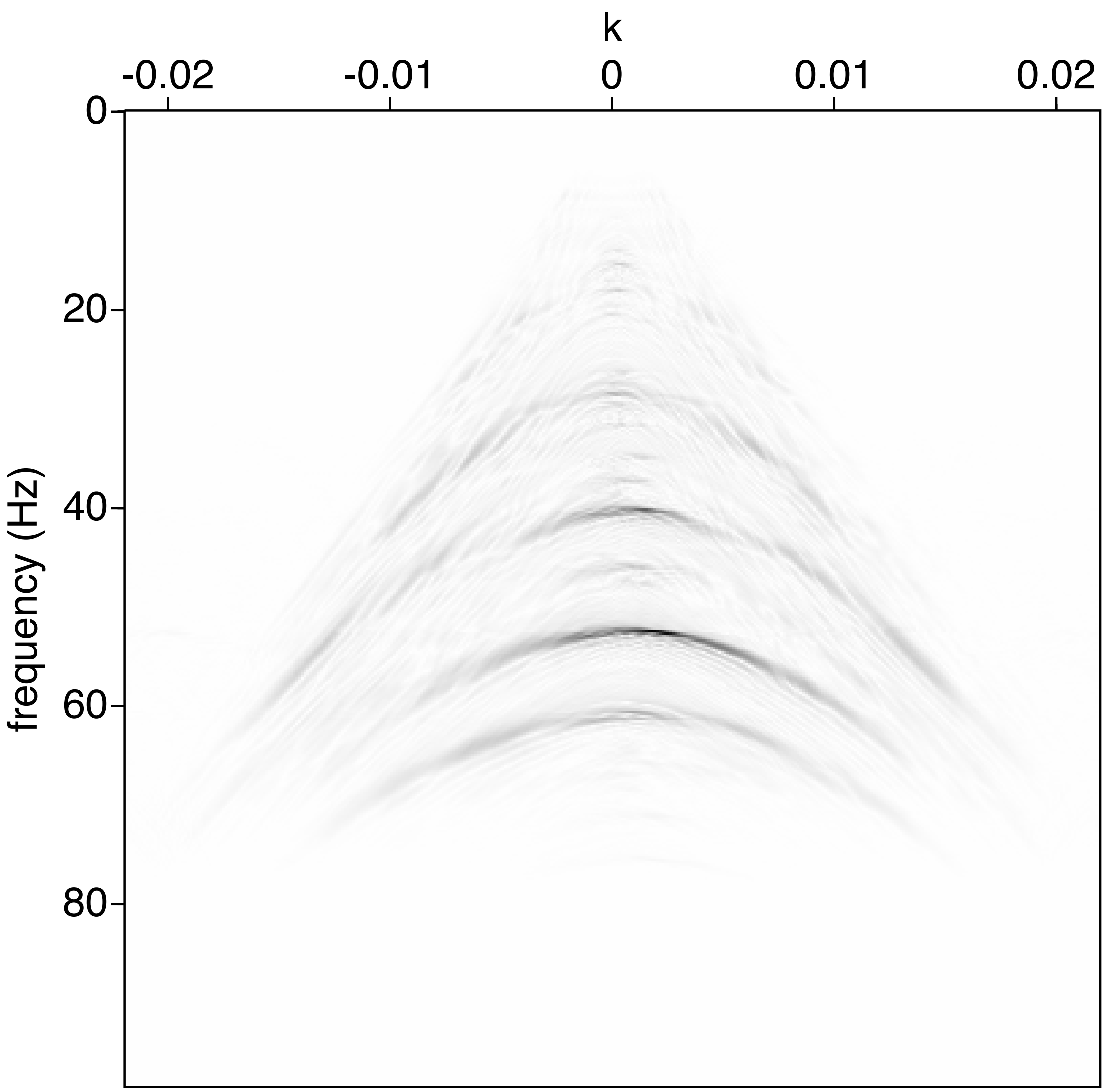
- *combination* with imaging (via sparse migration, see Tu)
- extension to 3D (via *dimensionality reduction*, see Bander)



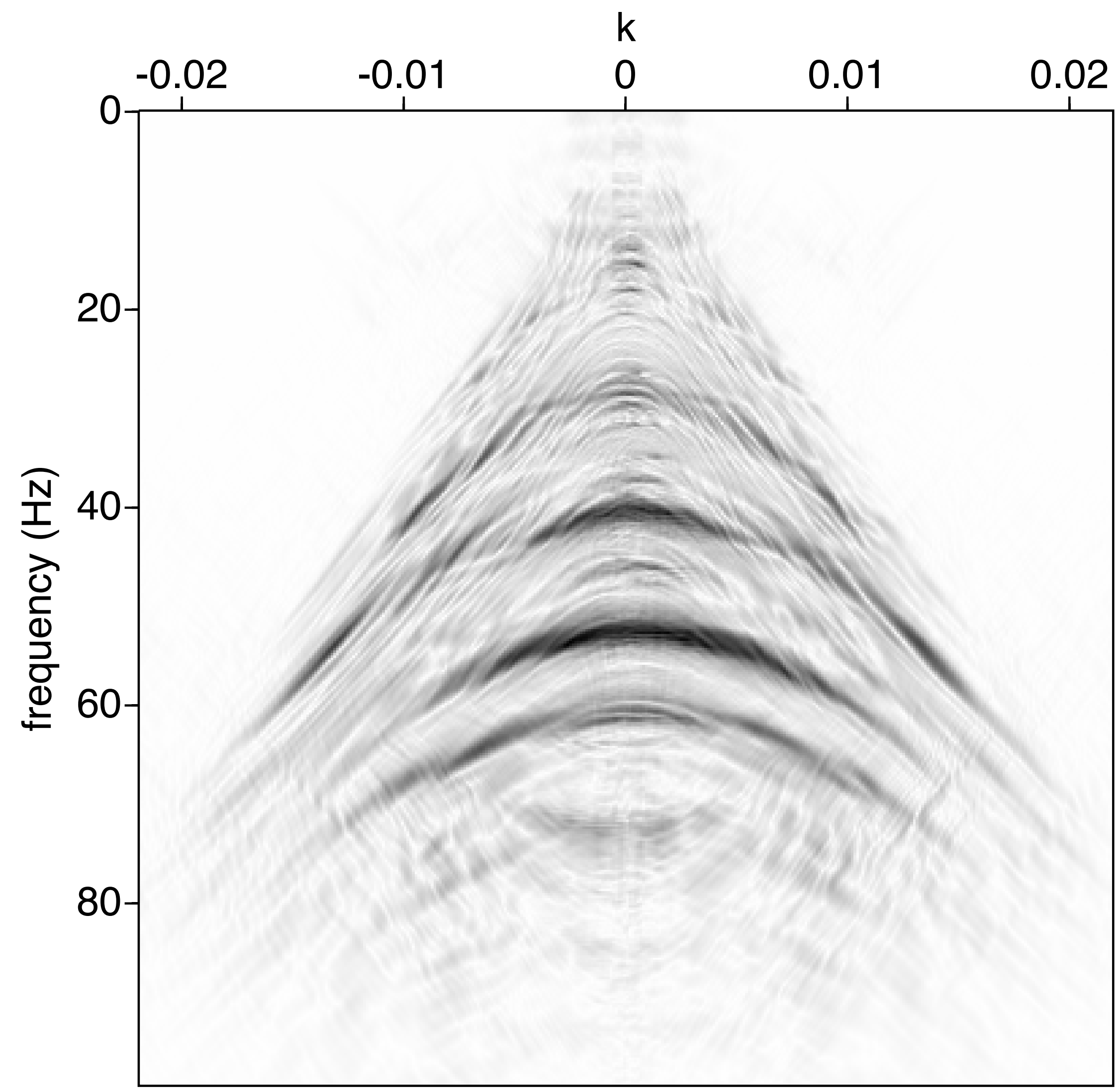
F-K Spectrum of data



F-K Spectrum of REPSI+Transform Primary IR



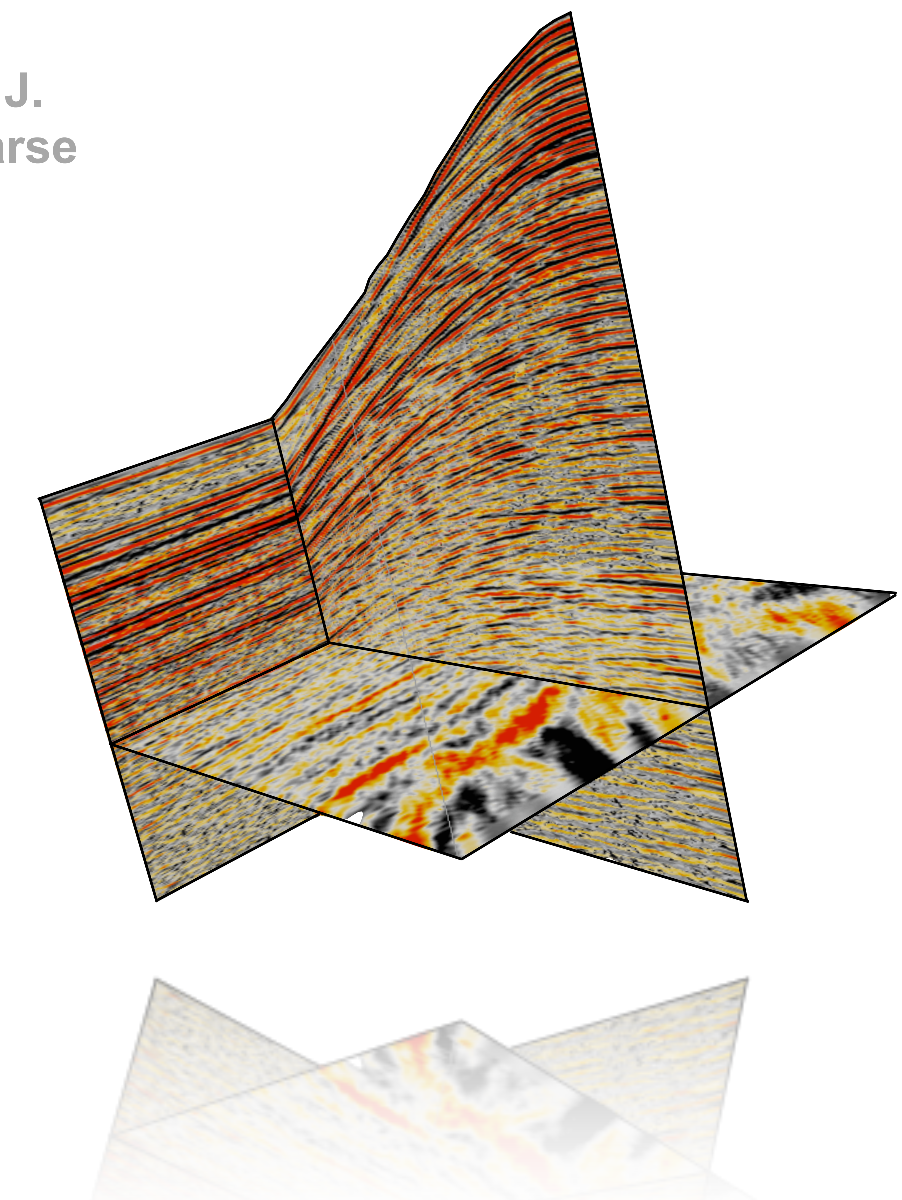
F-K Spectrum of data



F-K Spectrum of REPSI+Transform
Primary IR

Interferometric redatuming by *sparse* inversion

Joost van der Neut, Kees Wapenaar, an Felix J. Herrmann. Interferometric redatuming by sparse inversion. In preparation.



Key contributions

Robust formulation of *interferometric* imaging, exploiting *convex* (one-norm) and *sparse* (curvelets) structure to

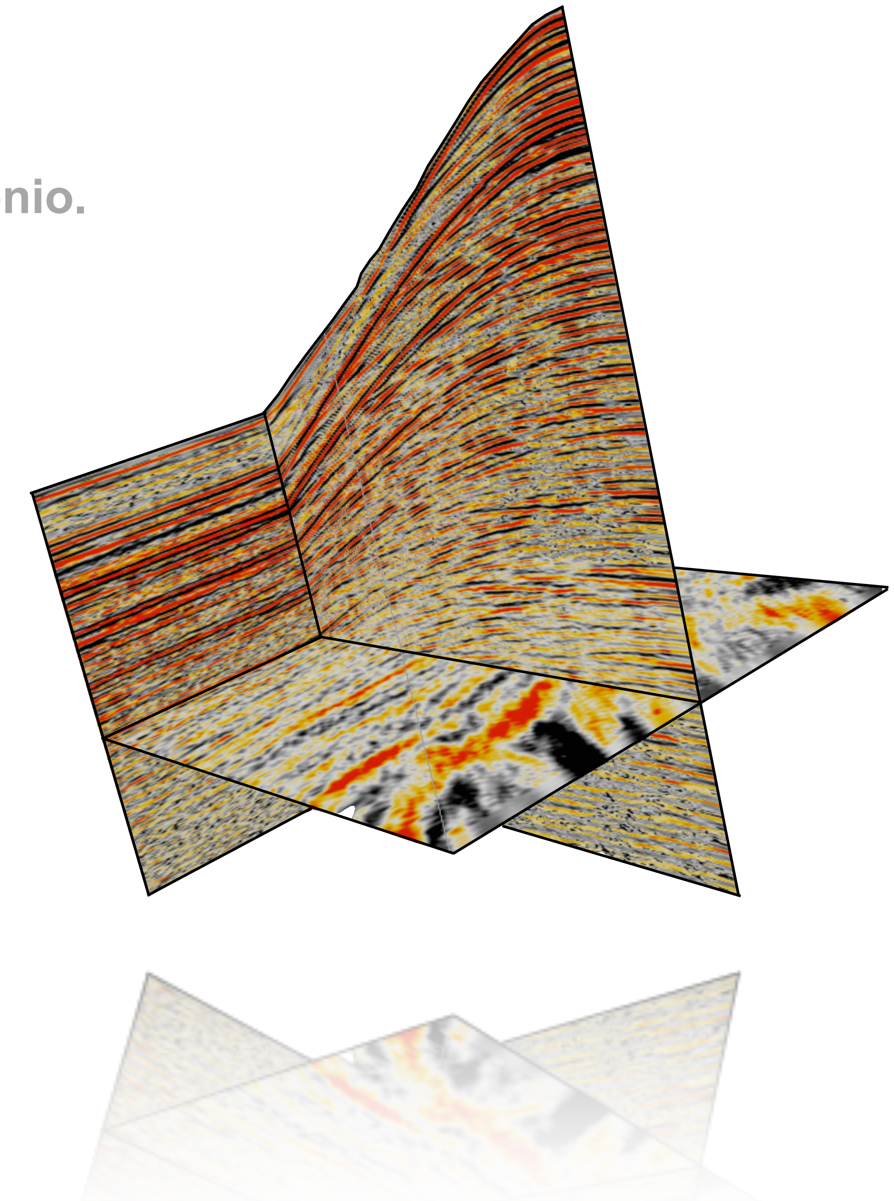
- compute *up-/down*-decompositions from *noisy* pressure data
- estimate *redatumed* upgoing *Green's* function

Opportunities & challenges

- combination with *sparse* imaging (see Tu Ning)
- incorporation *up-down*-decomposition in EPSI
- extension to *passive* data & 3D

Migration from surface-related multiples

Ning Tu, Tim T.Y. Lin, and Felix J. Herrmann. Migration with surface-related multiples from incomplete seismic data. SEG 2011, San Antonio.



Key contributions

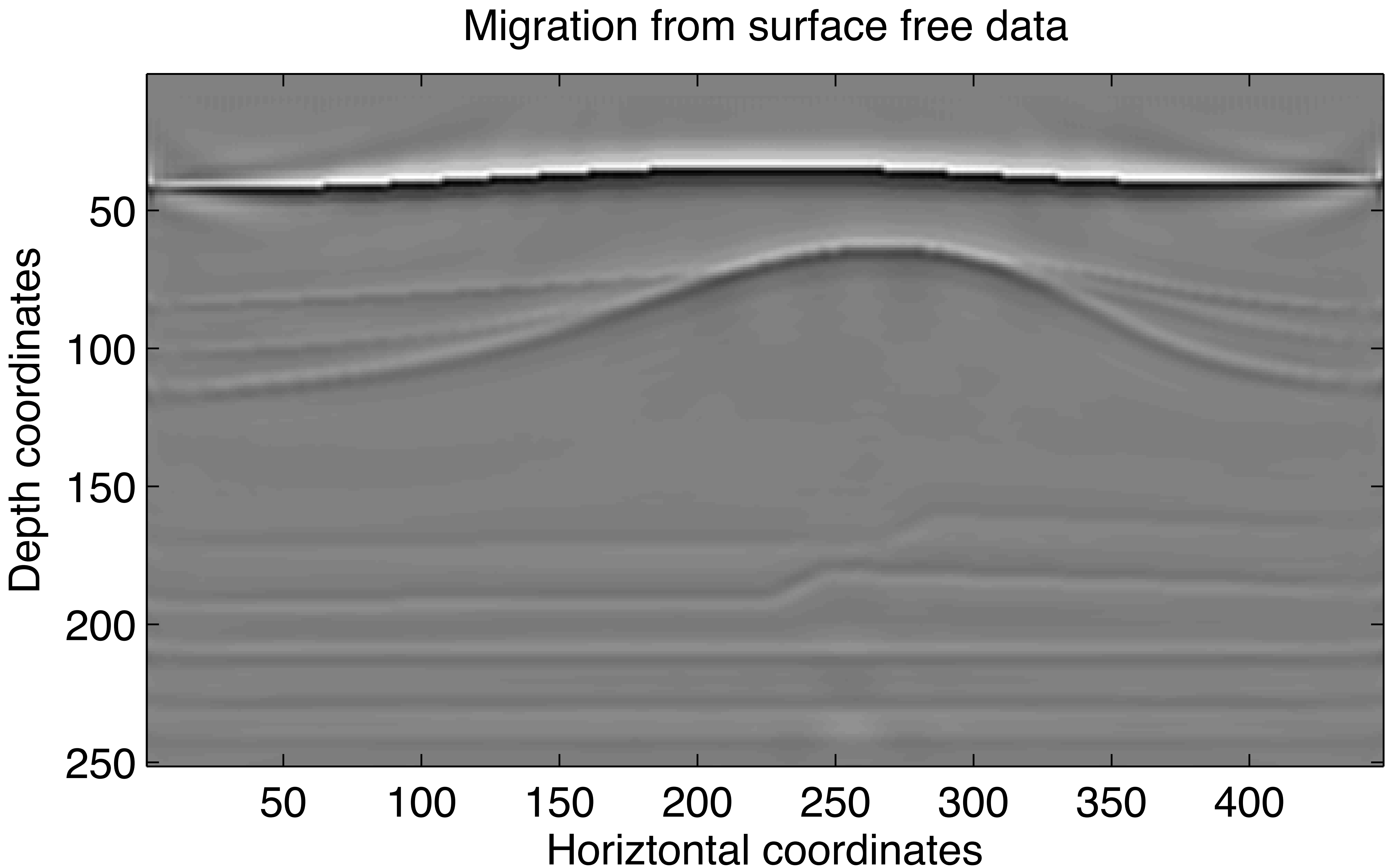
Combination of EPSI with sparsity-promoting imaging

- exploits *image*-space sparsity *adaptively* (velocity)
- considerable *speedup* from *wave* simulator

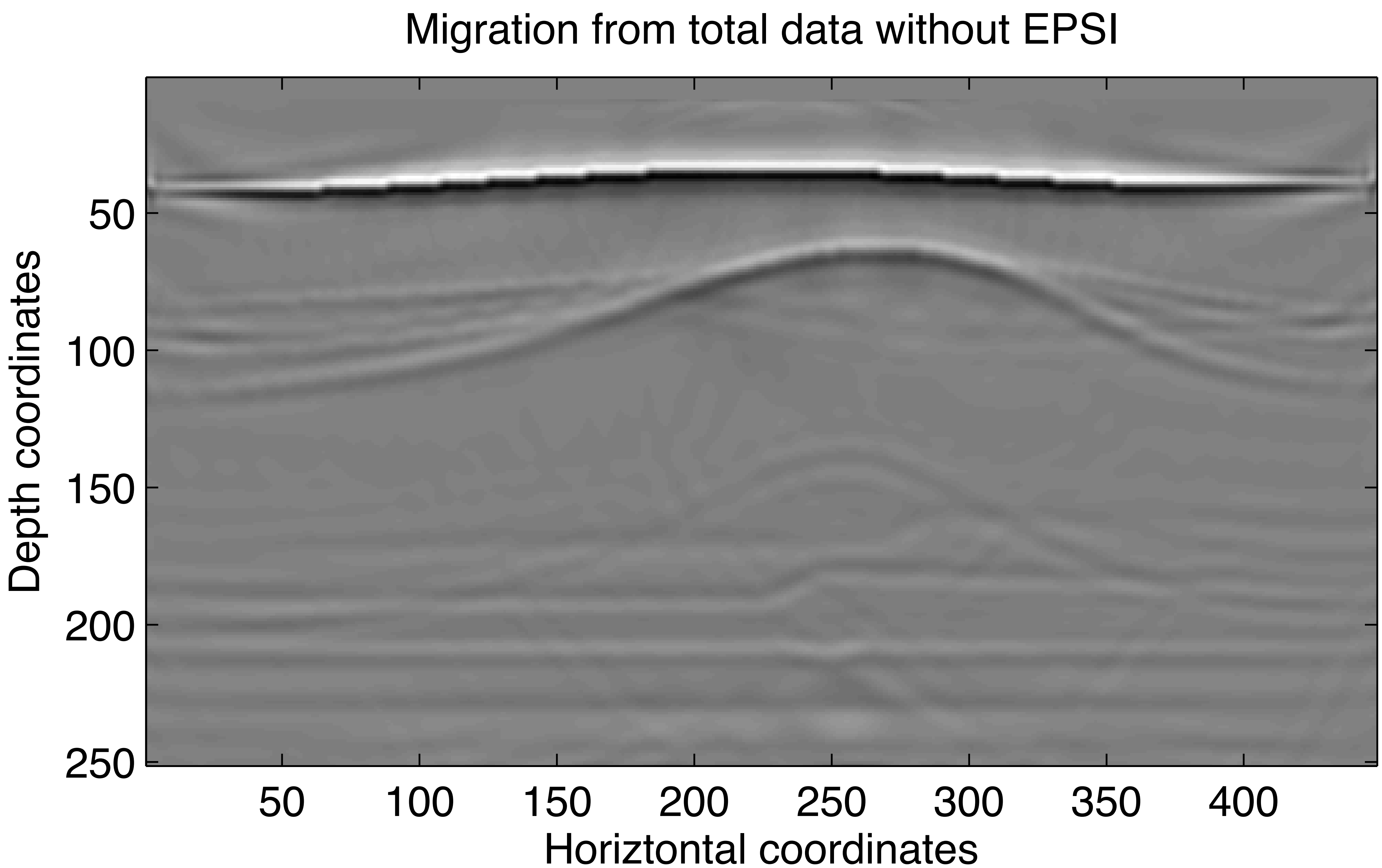
Opportunities & challenges

- development of *practical* workflows for *incomplete* data (e.g randomly distributed OB transducers)
- incorporation of *source*-function *estimation*
- *extension* to 3D

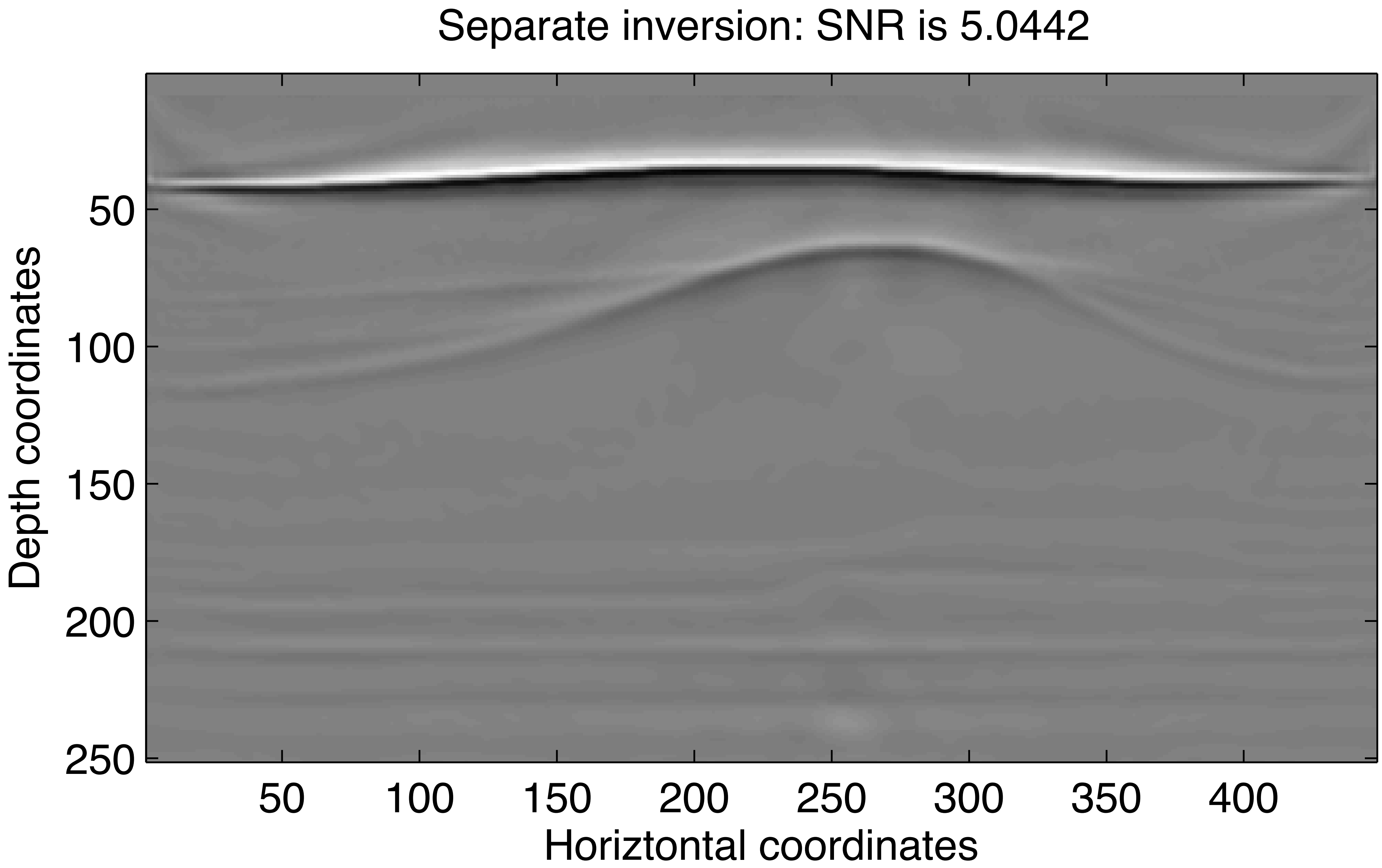
Complete data



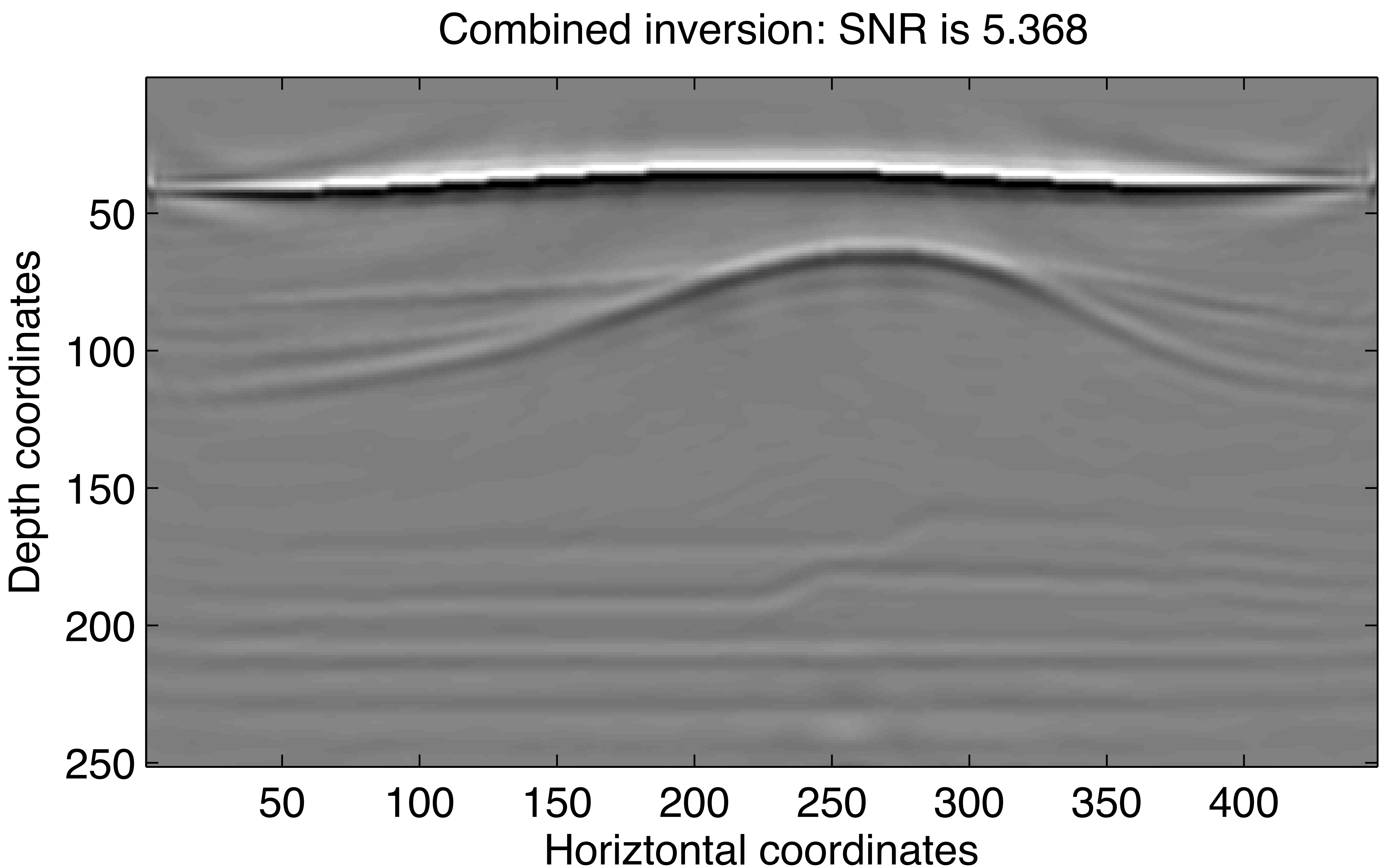
Complete data



Incomplete data (10%)

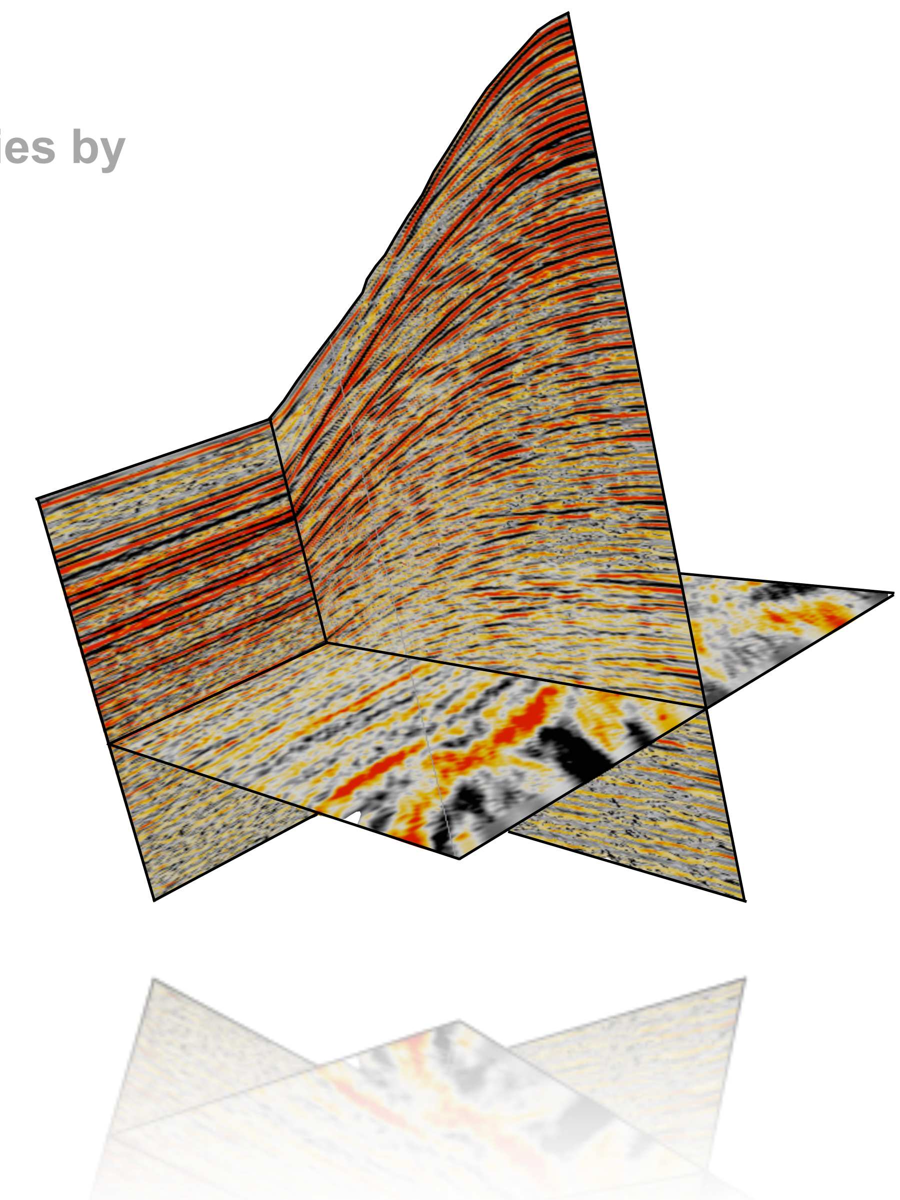


Incomplete data (10%)



Dimensionality-Reduced EPSI

Bander Jumah and Felix J. Herrmann. Dimensionality-reduced estimation of primaries by sparse inversion. SEG 2011, San Antonio



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Key contributions

Randomized dimensionality reduction of EPSI decreases storage and computation costs of matvec with dense matrices

- address *problematic* data handling by *parallel* architectures
- exploits low-rankness of HSS *representations* data matrix

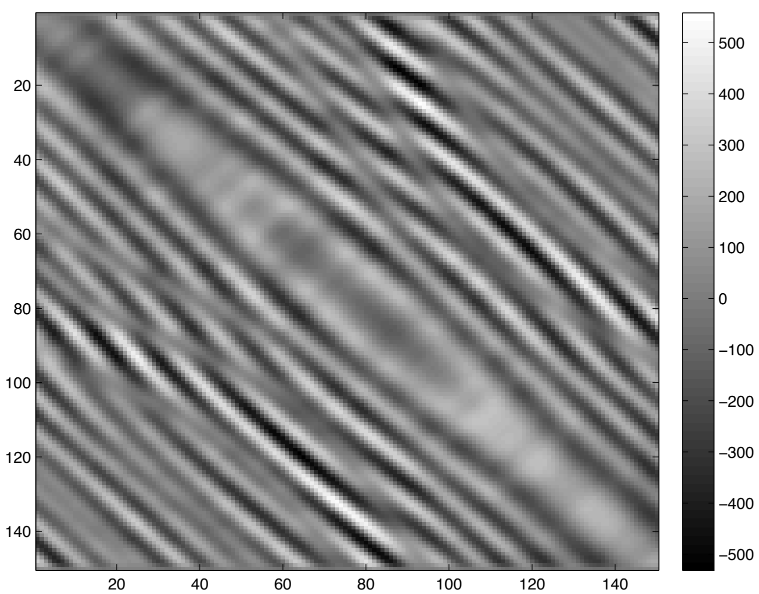
Opportunities & challenges

- combination with low-rank matrix factorization
- avoidance of on-the-fly missing shot interpolation
- extension to 3D

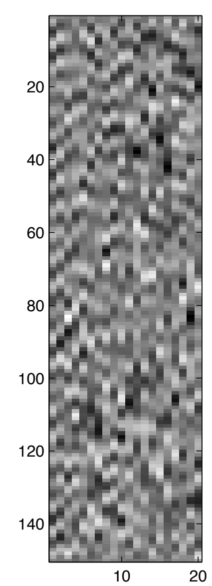
Dimensionality Reduction Via SVD

Approximate data matrix $\hat{\mathbf{P}}$ with *low-rank* factorization:

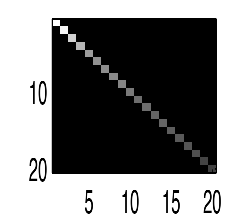
$$\hat{\mathbf{P}} \approx \mathbf{U} * \mathbf{\Sigma} * \mathbf{V}^*$$



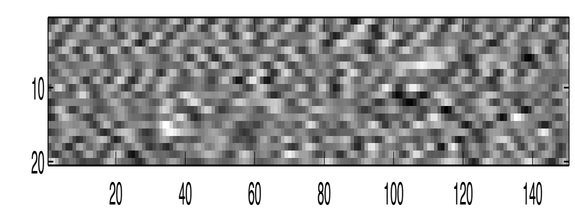
$n_r \times n_s$



$n_r \times k$



$k \times k$



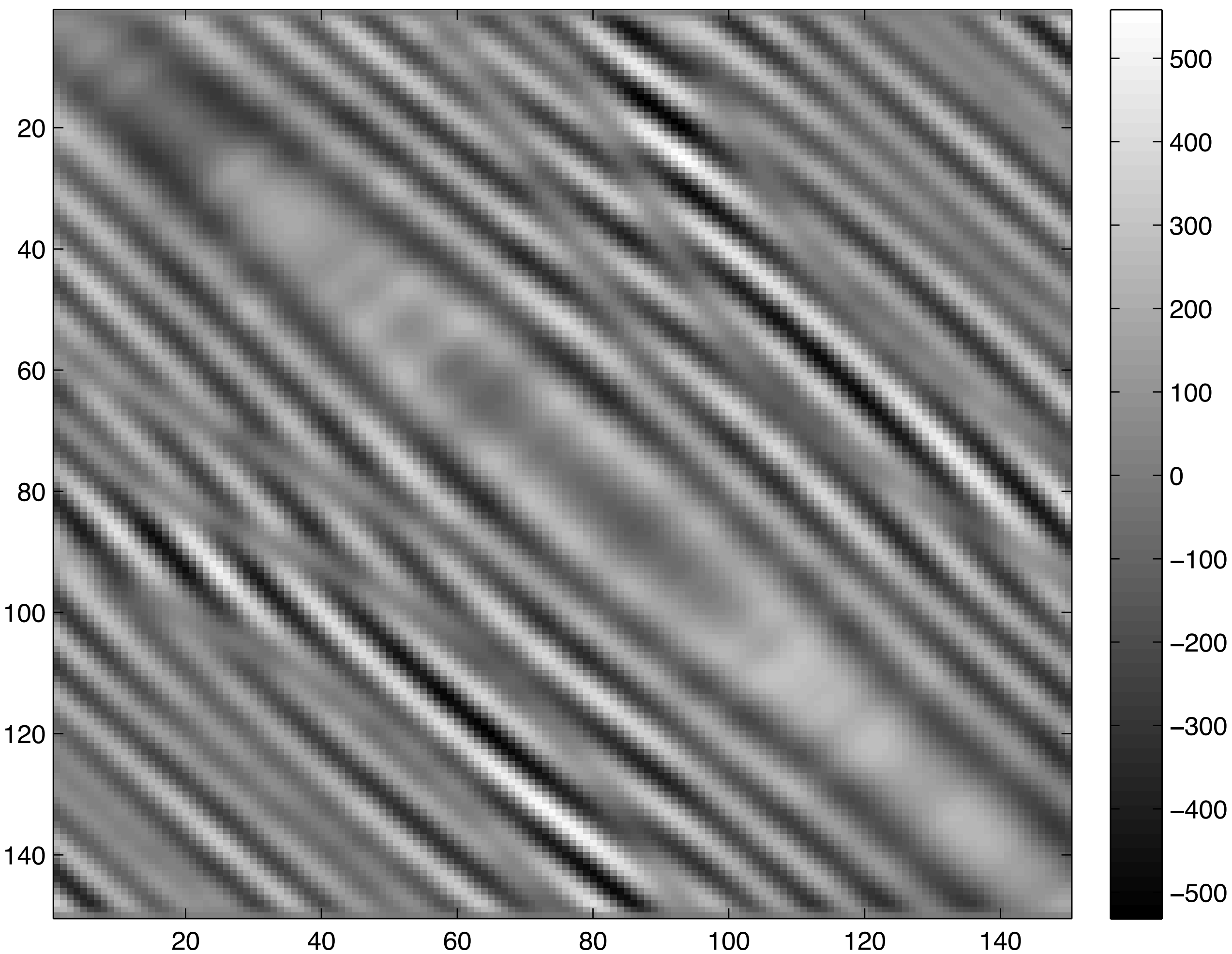
$k \times n_s$

k : approximate rank

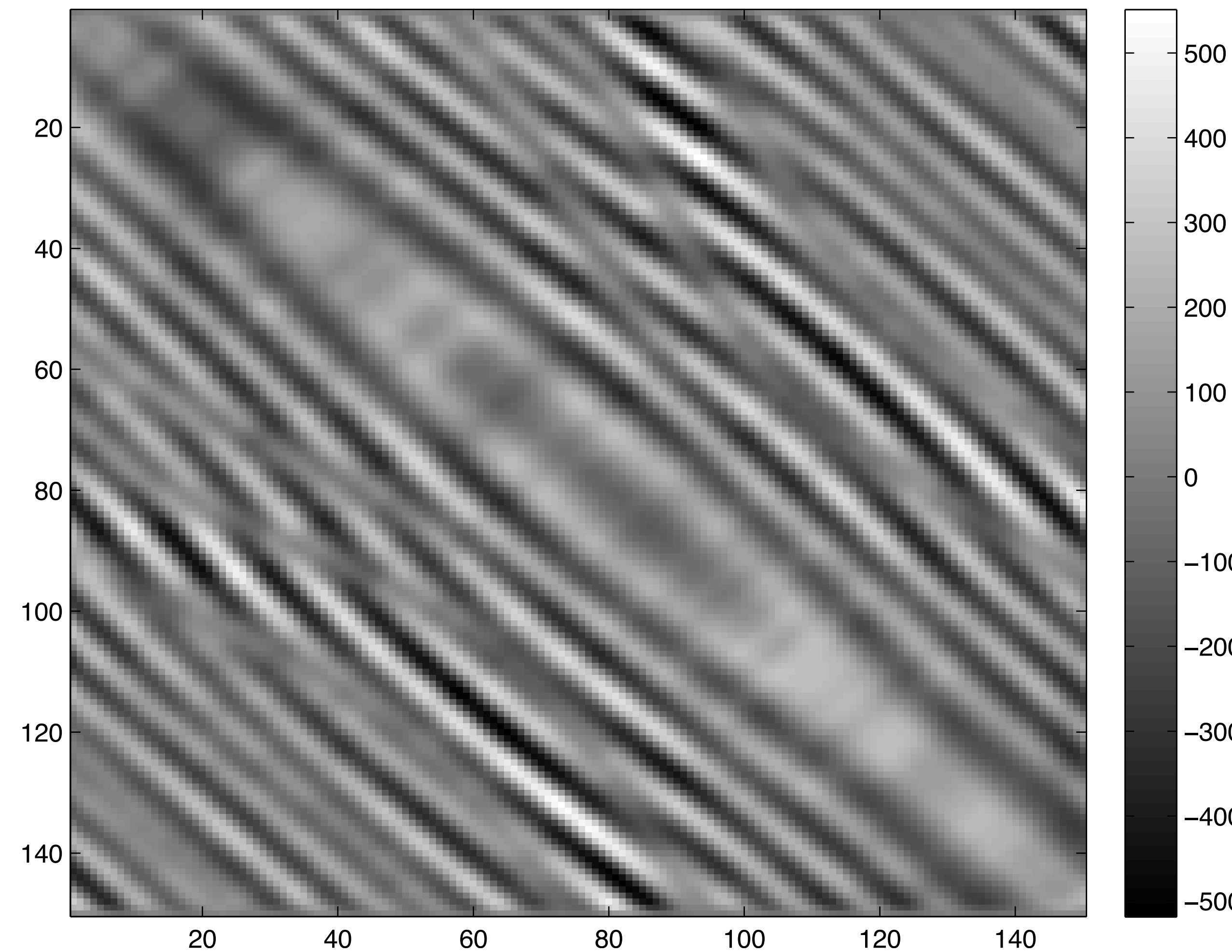
$k << min(n_r, n_s)$

Full vs approximated data

$\hat{\mathbf{P}}$



Approximated $\hat{\mathbf{P}}$



$$n_s = n_r = 150$$
$$k = 20 = 14\%$$
$$SNR = 16dB$$

Outcomes

Versatile implementation incorporating latest developments

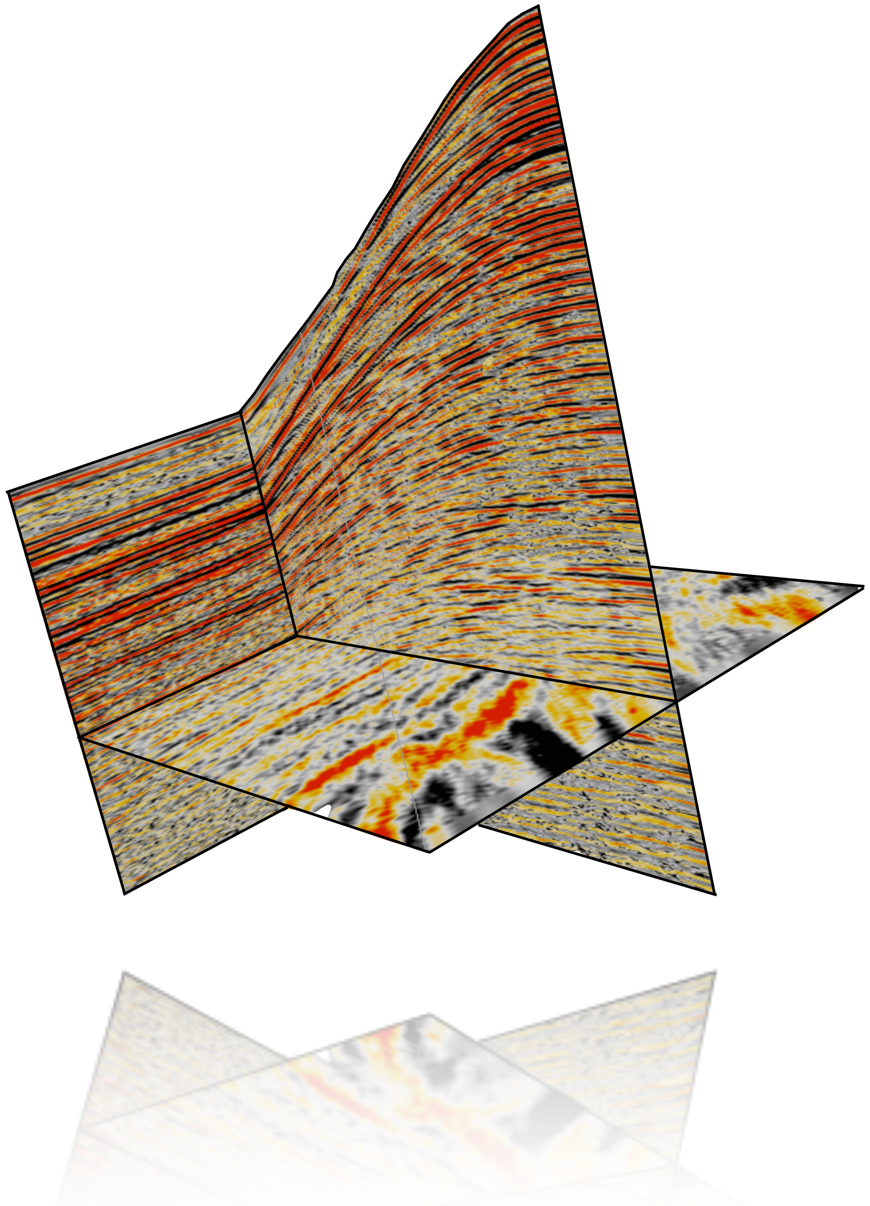
- in large-scale *convex* optimization
- *sparsifying* transforms

Opportunity to include matrix *factorization* and other *convex* and *robust* norms

Uptake by industry

- keen interest from PGS, BP, and Chevron
- evaluation by WesternGeco & BG

Theme III: Efficient imaging



SLIM

Key strategy

Leverage dimensionality reduction techniques that exploit

- *separable* structure of seismic imaging
- *sparsity* of migrated images
- properties of Pareto trade off curves

Efficient & computable algorithms that work on small data subsets

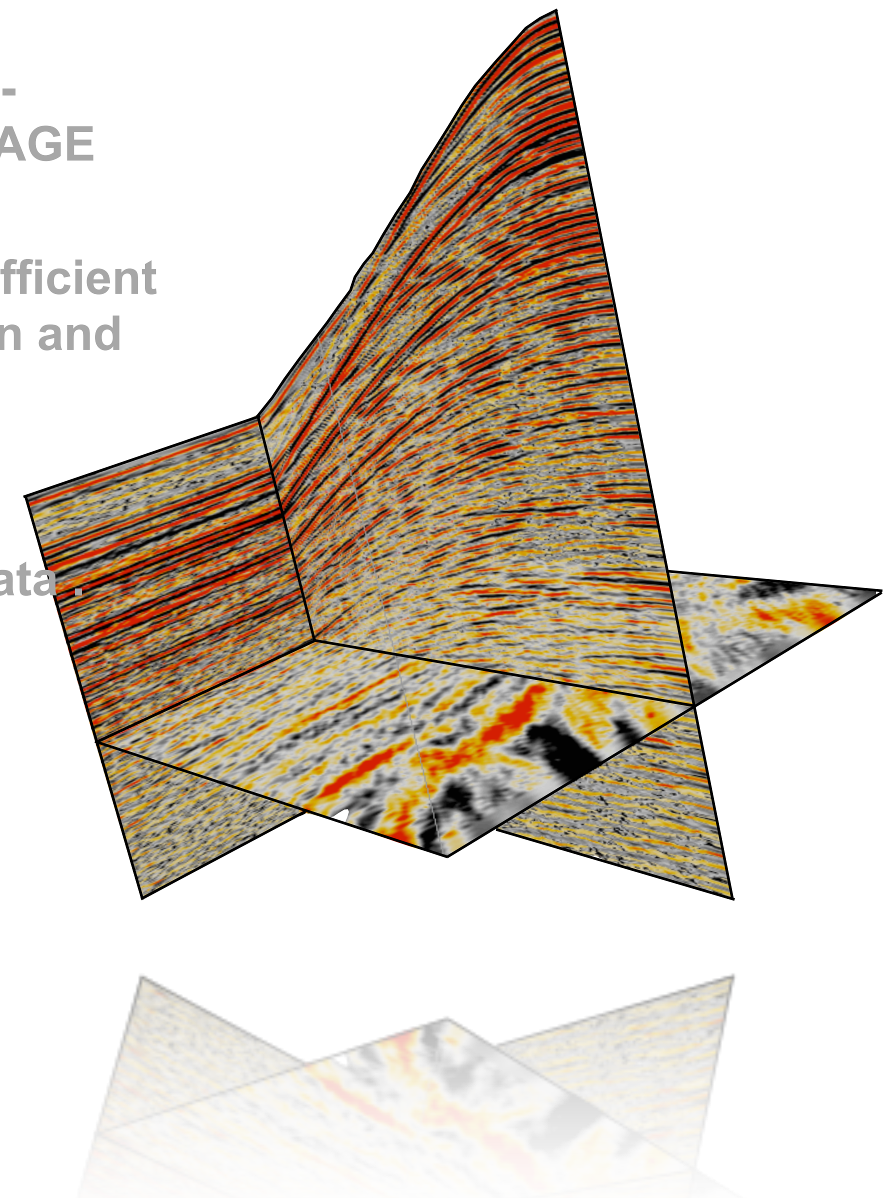
- leverage sparsity promotion in imaging
- form and compute gradients for true image volumes

Efficient least-squares imaging with sparsity promotion and *compressive* sensing

Felix J. Herrmann and Xiang Li. Efficient least-squares migration with sparsity promotion. EAGE 2011, Vienna.

Felix J. Herrmann and Xiang Li. TR-2011-03. Efficient least-squares imaging with sparsity promotion and compressive sensing. To appear Geophysical Prospecting.

Aleksandr Aravkin and Xiang Li and Felix J. Herrmann. Fast seismic imaging for marine data. Submitted to ICASSP 2012.



Key contributions

Efficient implementation of *sparsity*-promoting imaging that

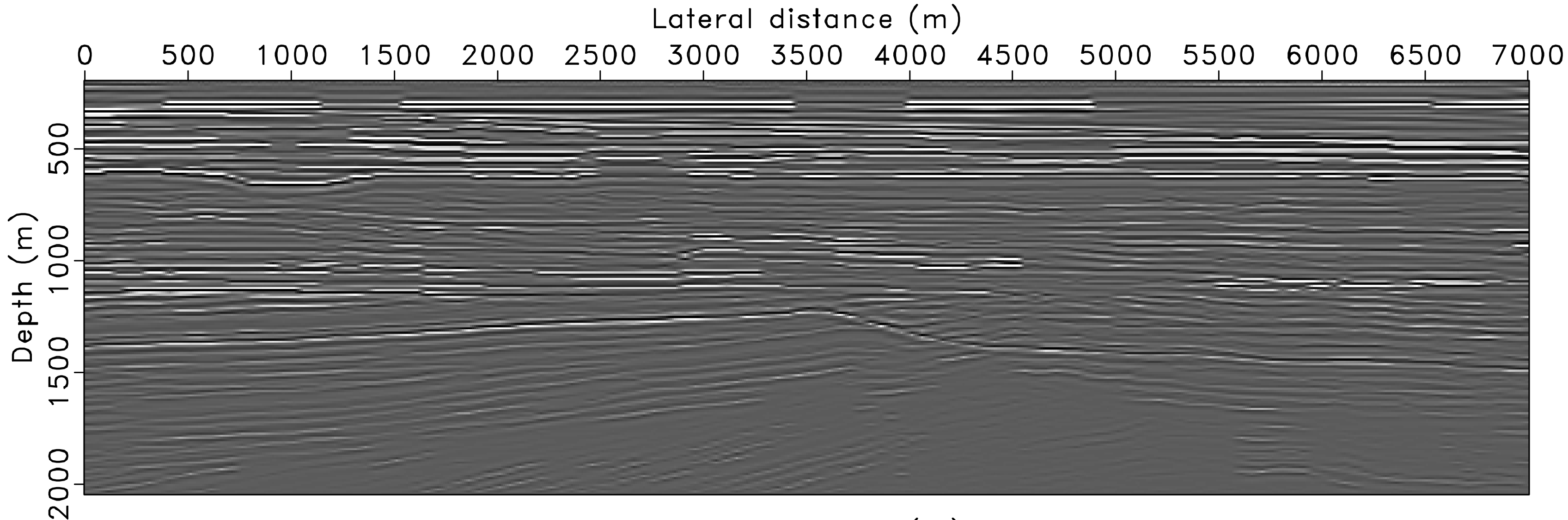
- works on small *randomized* collections of sim./seq. shots
- uses curvelet *sparsity* to *remove* artifacts
- regularizes the *null* space of the *imaging* operator

Opportunities & challenges

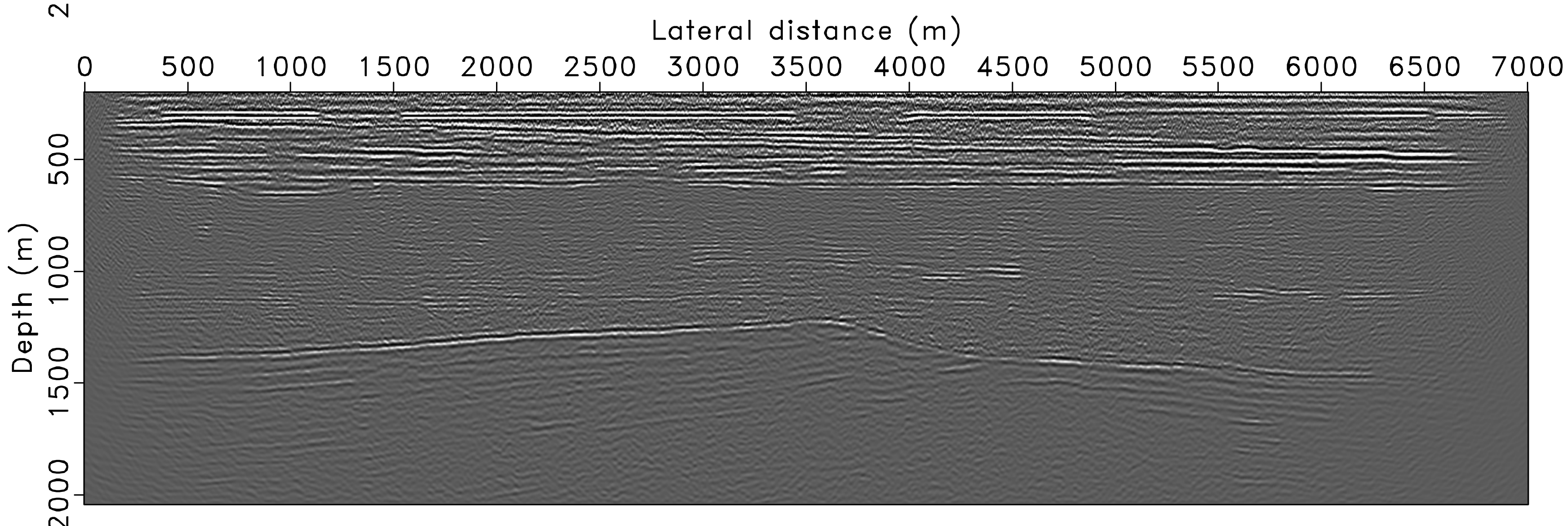
- *rigorous* theory for optimization with *redraws*
- *extension* to image volumes
- extension to 3D

BG compass model

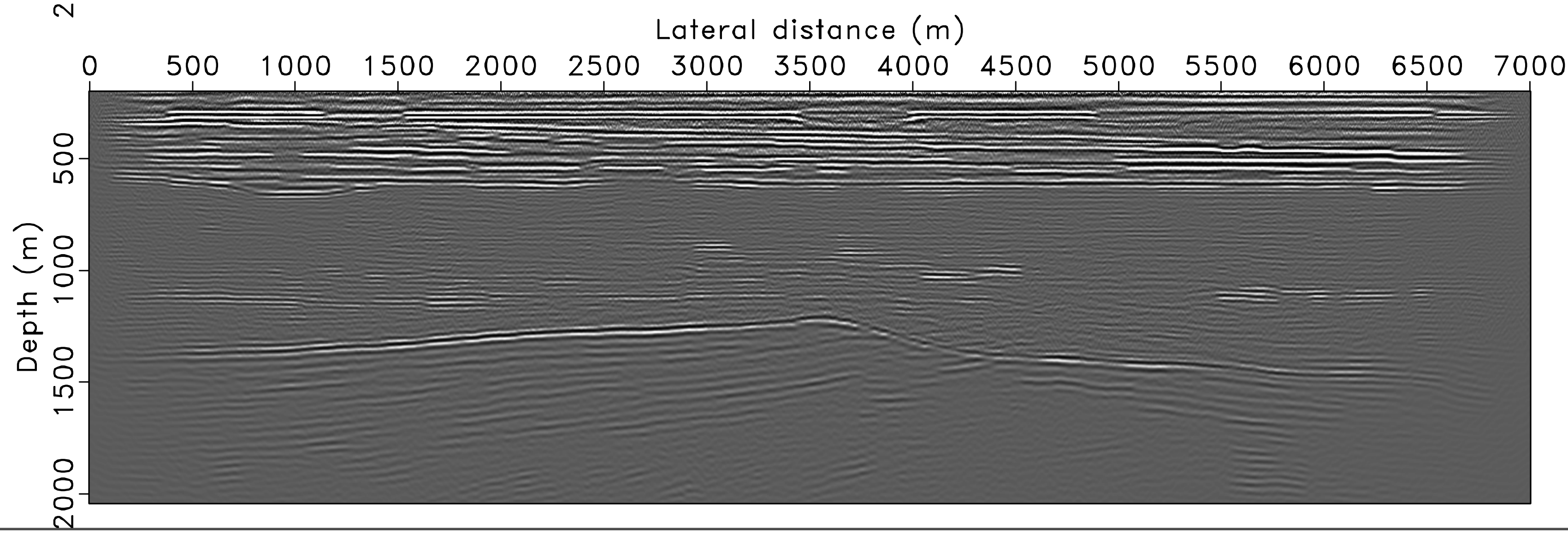
True perturbation



Imaged w/o renewals

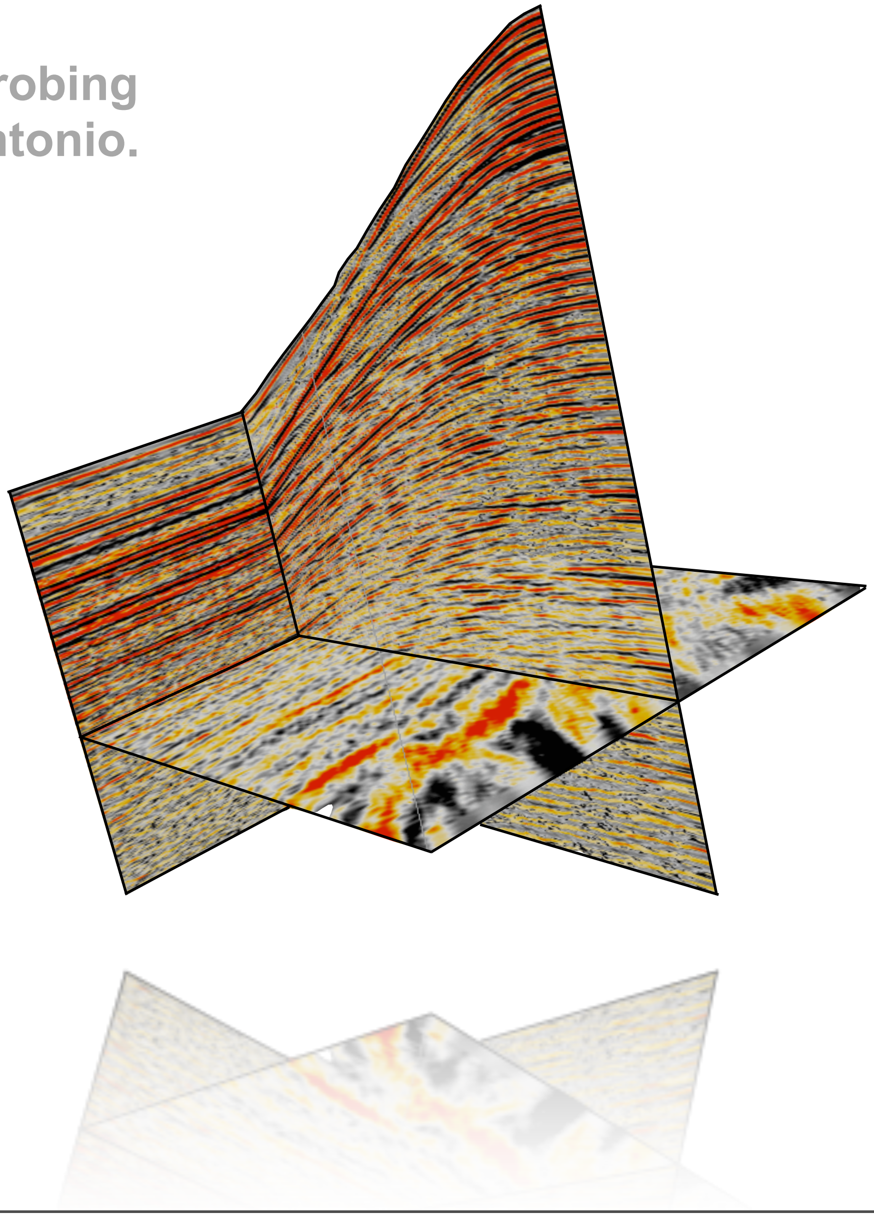


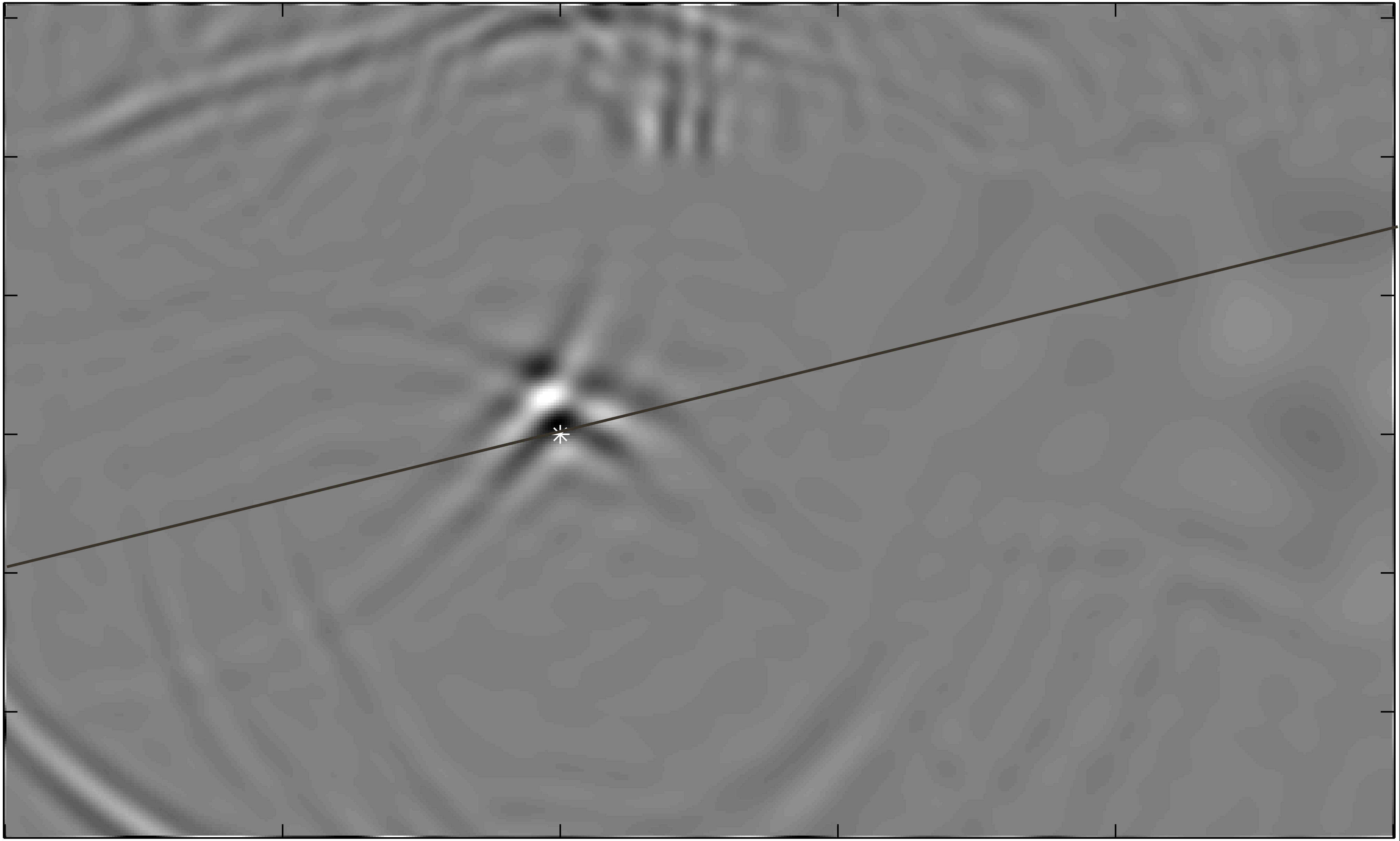
Imaged with renewals

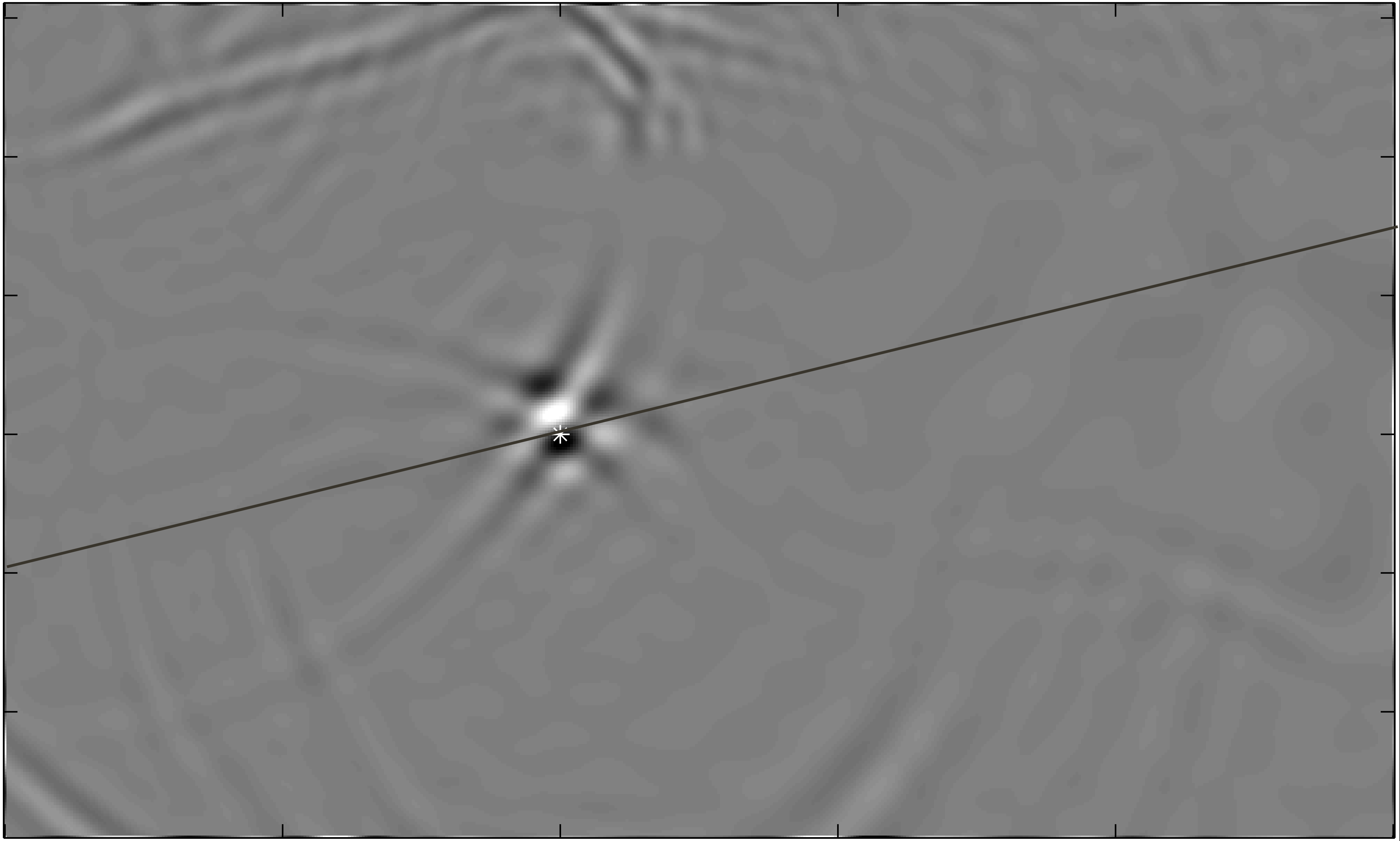


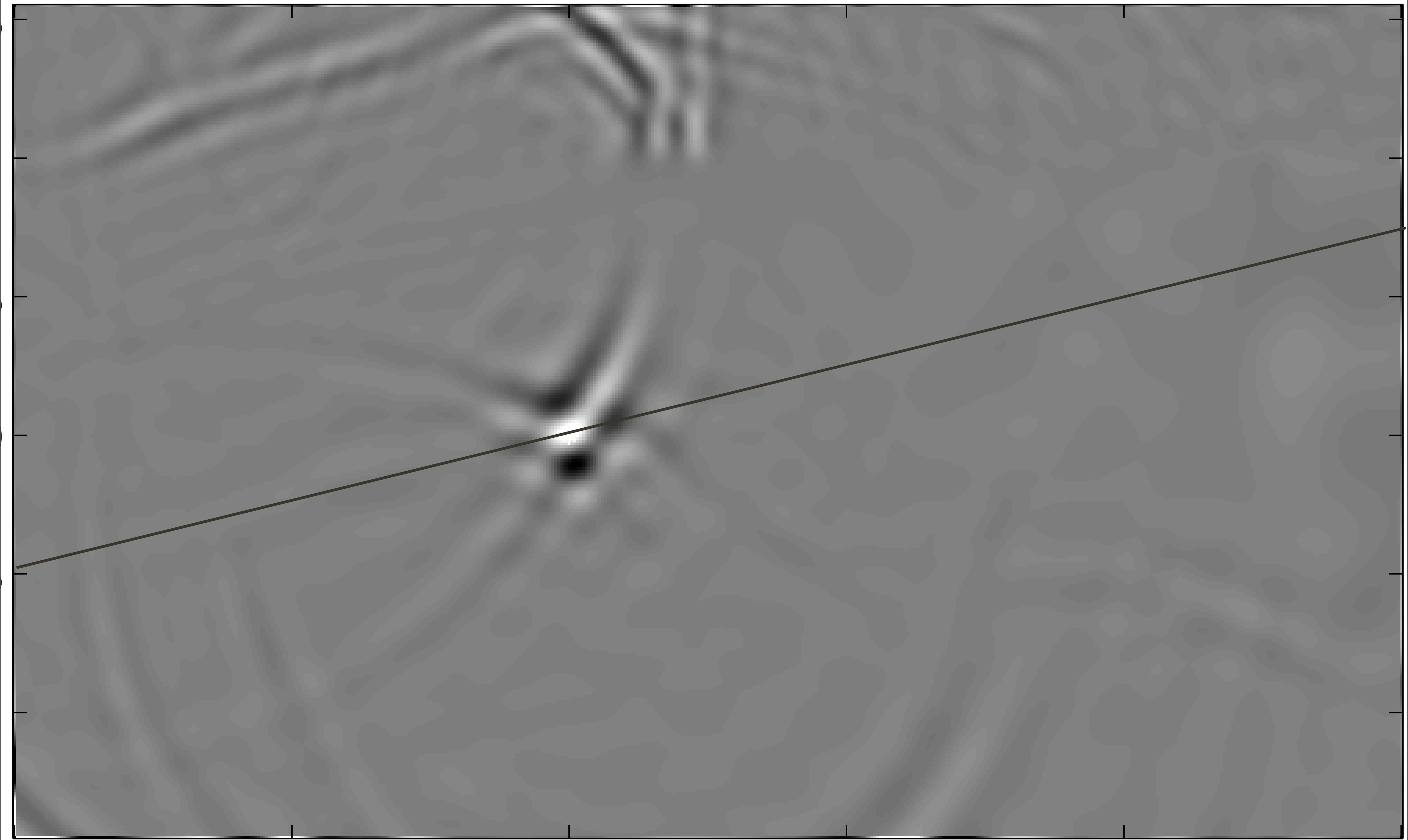
Probing the *extended* image volume

Tristan van Leeuwen and Felix J. Herrmann. Probing the extended image volume. SEG 2011, San Antonio.

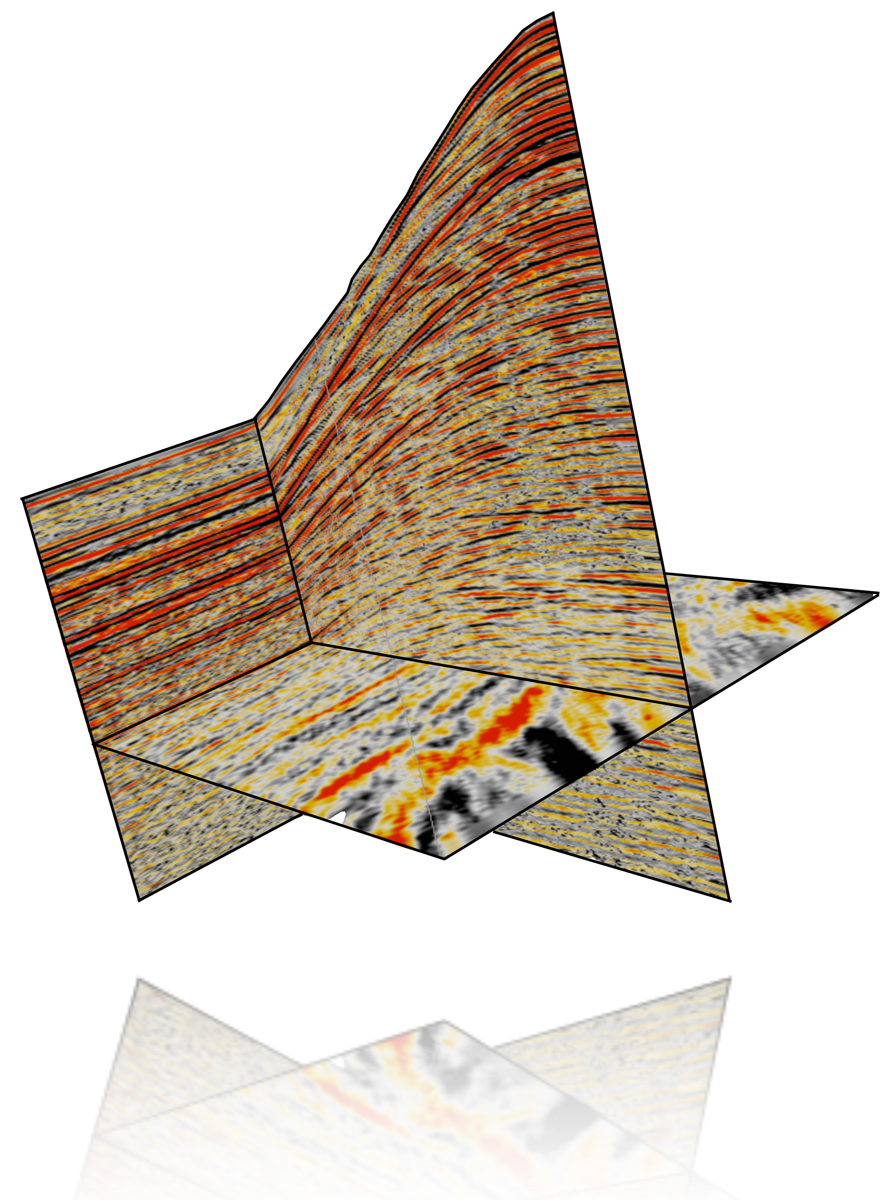








Theme IV: Efficient & robust FWI



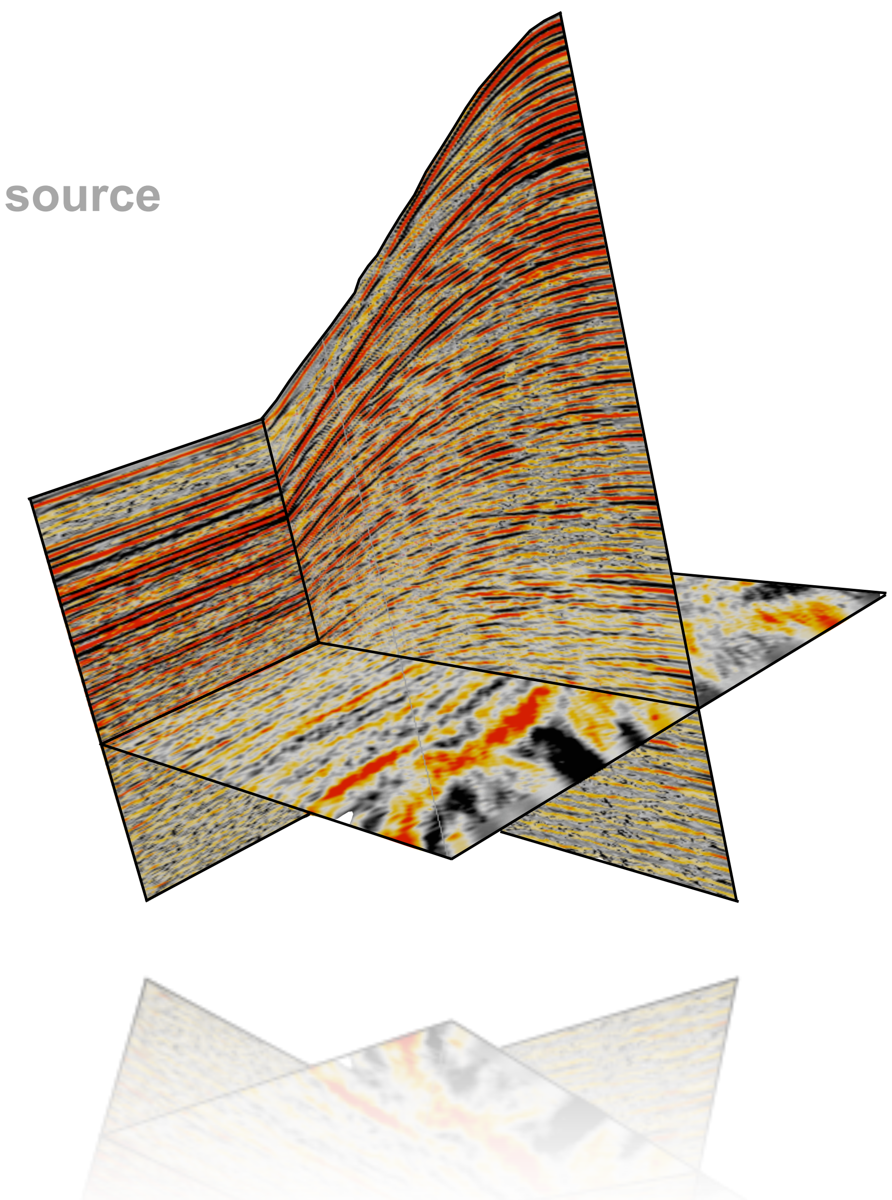
Key strategies

Leverage dimensionality reduction techniques that control *errors* in the *gradients* by exploiting

- *separable* structure
  (growing mini batches & robust statistics)
- *multiscale* structure
  (transform-domain *sparsity* & convex optimization)
- *convex-composite* structure
  (compressive sensing)

Fast waveform inversion without source encoding

Tristan van Leeuwen and Felix J. Herrmann.
TR-2011-06. Fast waveform inversion without source encoding.



Key contributions

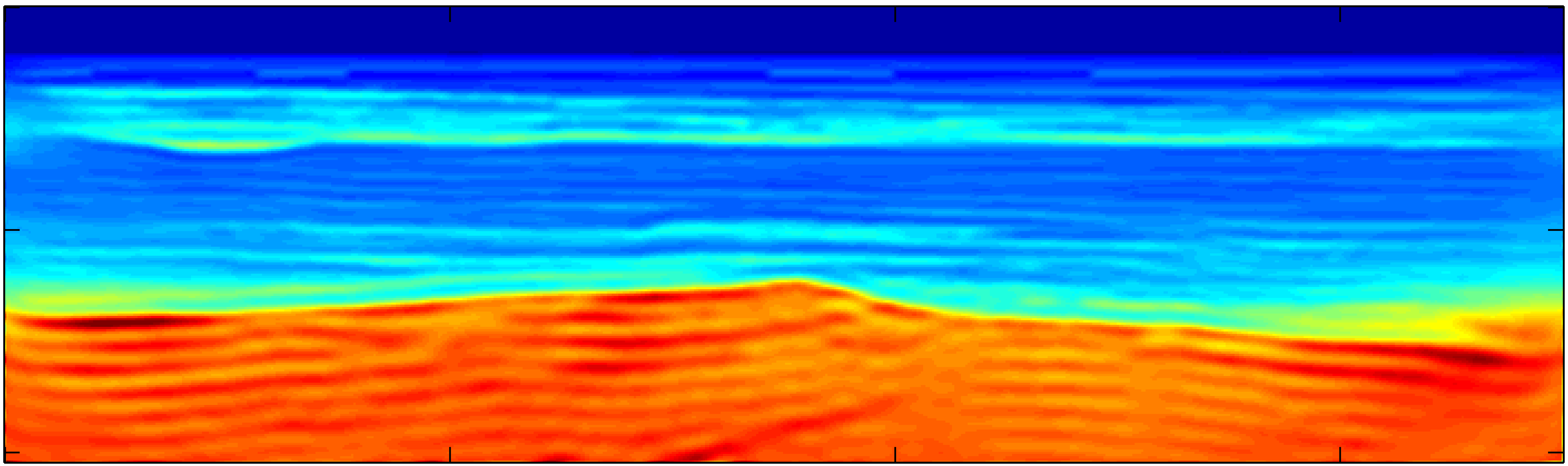
Randomized dimensionality *reduction* for *marine* acquisition

- growing mini batches consisting of *randomly* selected *sequential* shots
- control over error by drawing new batches in *combination* with *growing* batch size

Opportunities

- *adaptive* growing of the mini batch size
- implementation in 3D FWI
  (in collaboration with Mike Warner, Imperial College)

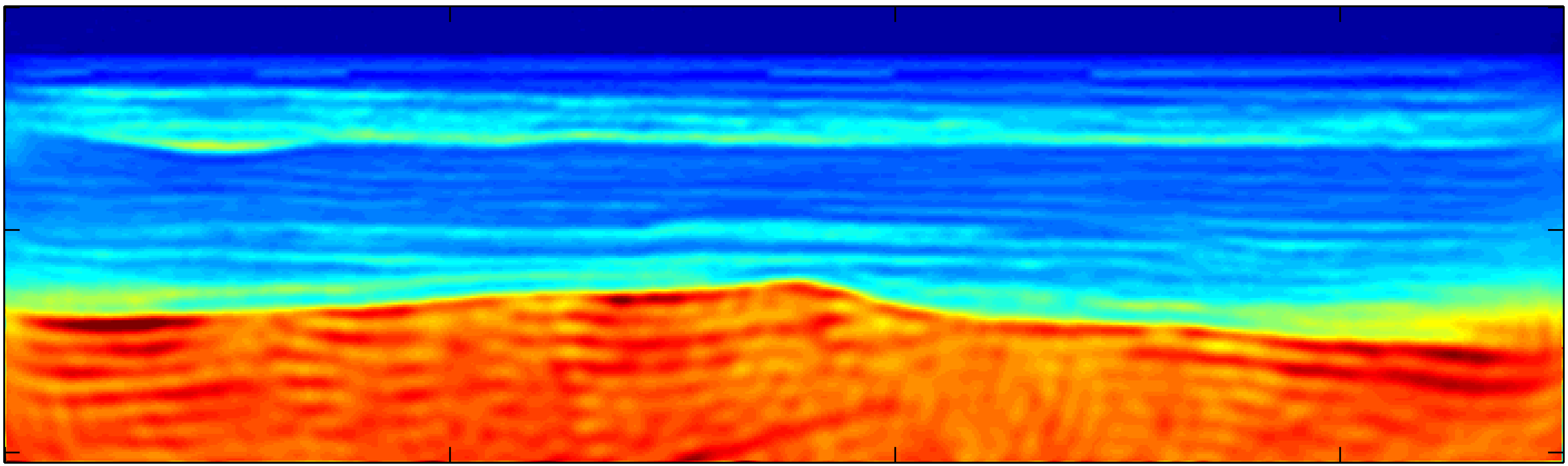
FWI



traditional L-BFGS

~10 full evaluations per frequency band

FWI



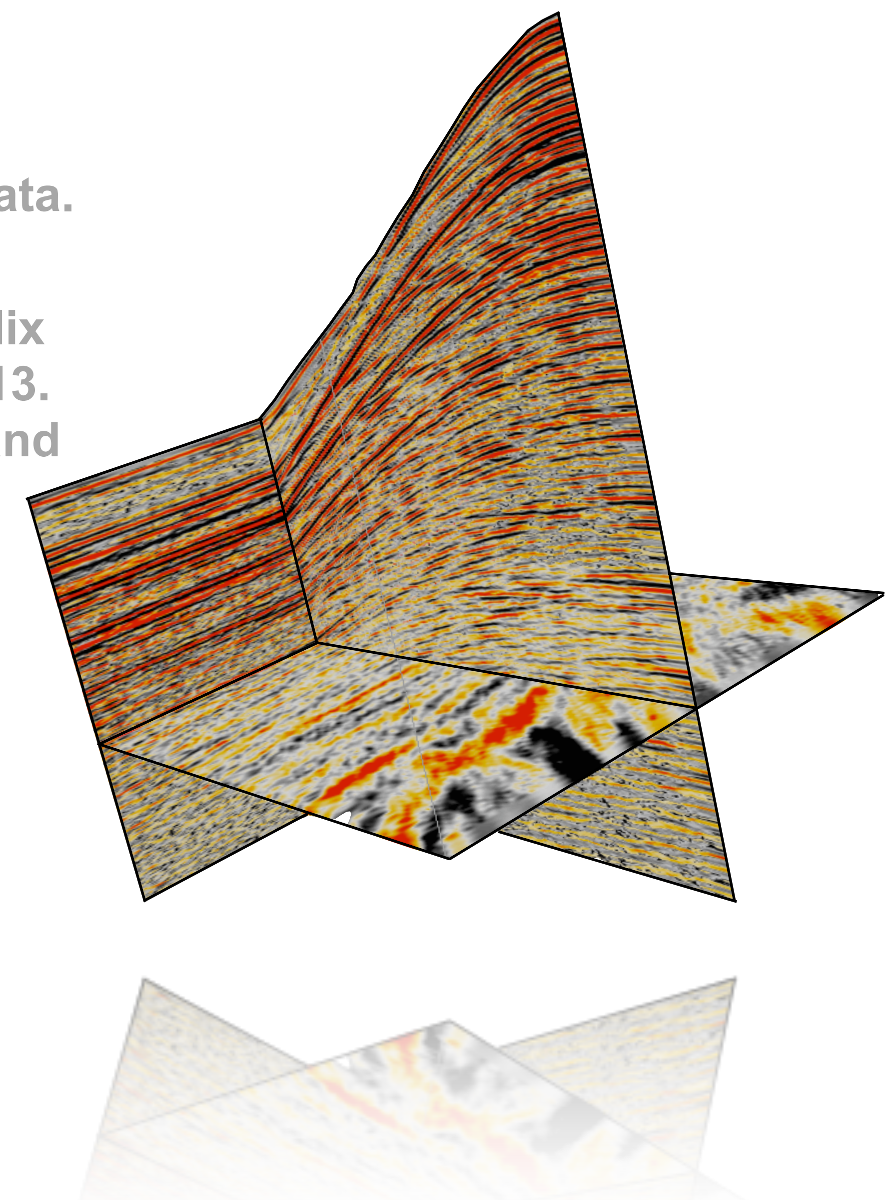
hybrid method

~2 full evaluations per frequency band

Robust FWI using Student's t

Aleksandr Aravkin and Xiang Li and Felix J. Herrmann. Fast seismic imaging for marine data. Submitted to ICASSP 2012.

Aleksandr Aravkin, Michael P. Friedlander, Felix Herrman, and Tristan van Leeuwen. TR-2011-13. Robust inversion, dimensionality reduction, and randomized sampling.



Key contributions

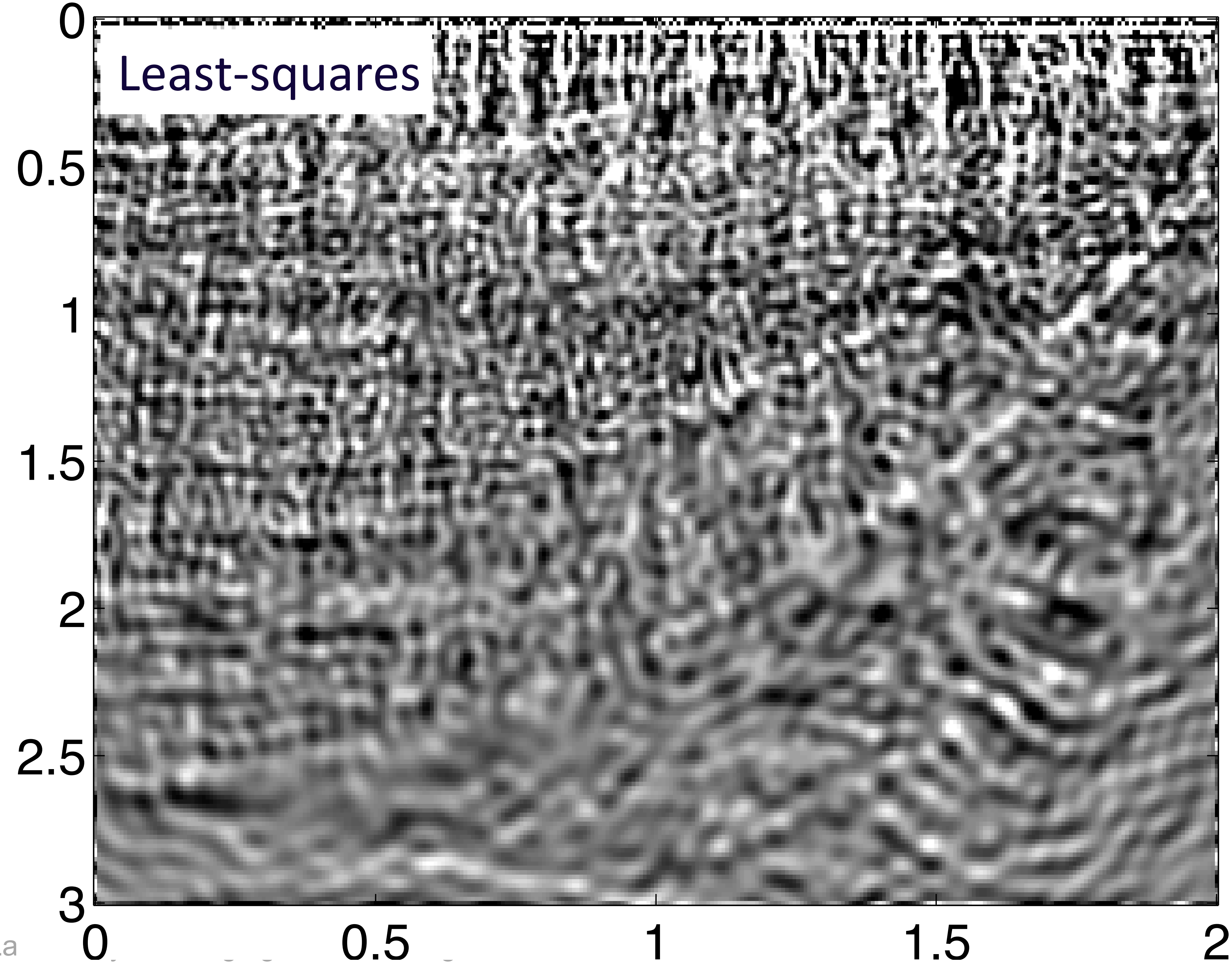
Incorporation of *robust* Student t penalty functional

- *insensitive* to outliers
- dimensionality reduction & source estimation

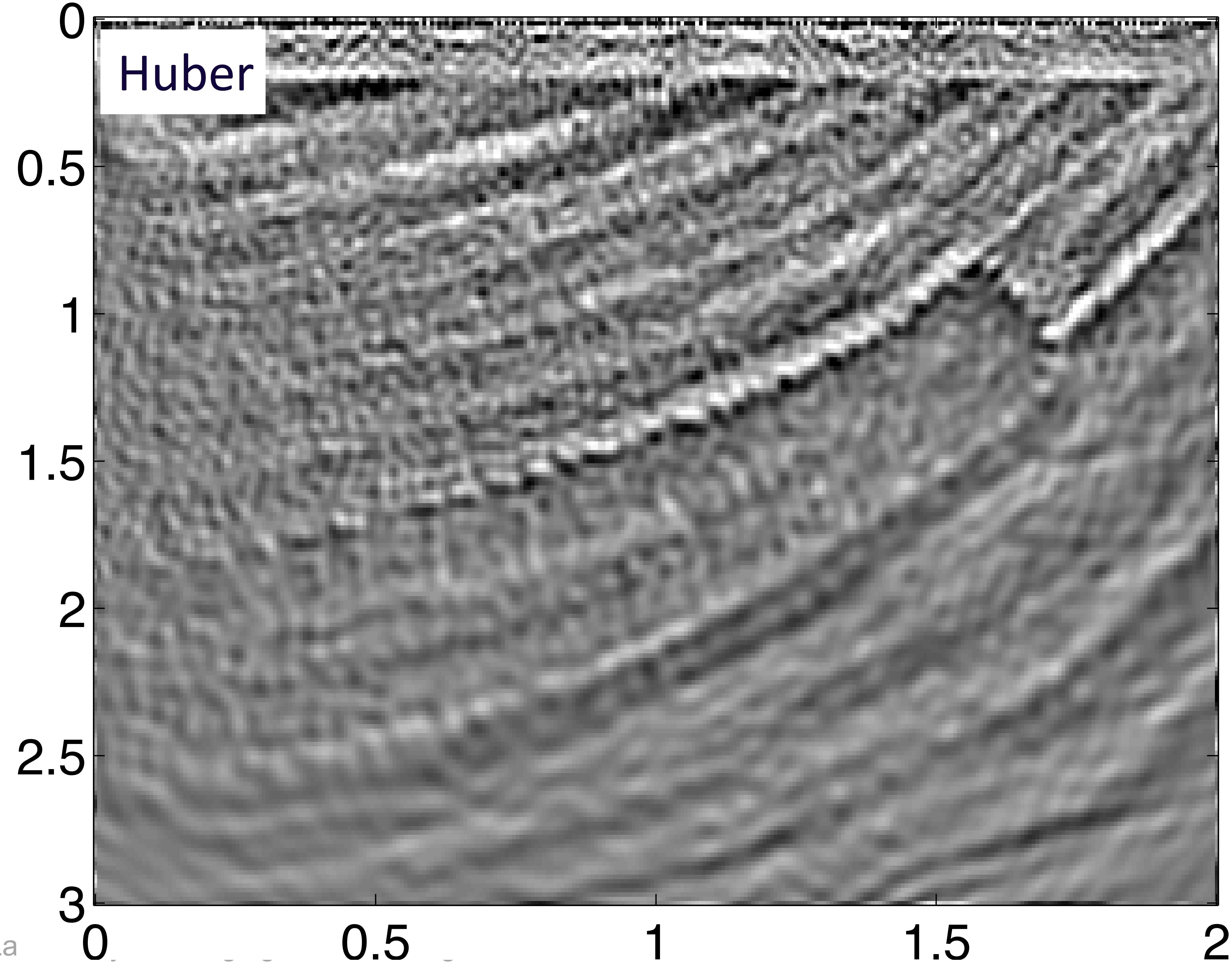
Opportunities & challenges

- testing for more *realistic* outliers (e.g. groundroll)
- strategy for *determining* the *hyper parameter*
- implementation in 3D FWI
  (in collaboration with Mike Warner, Imperial College)

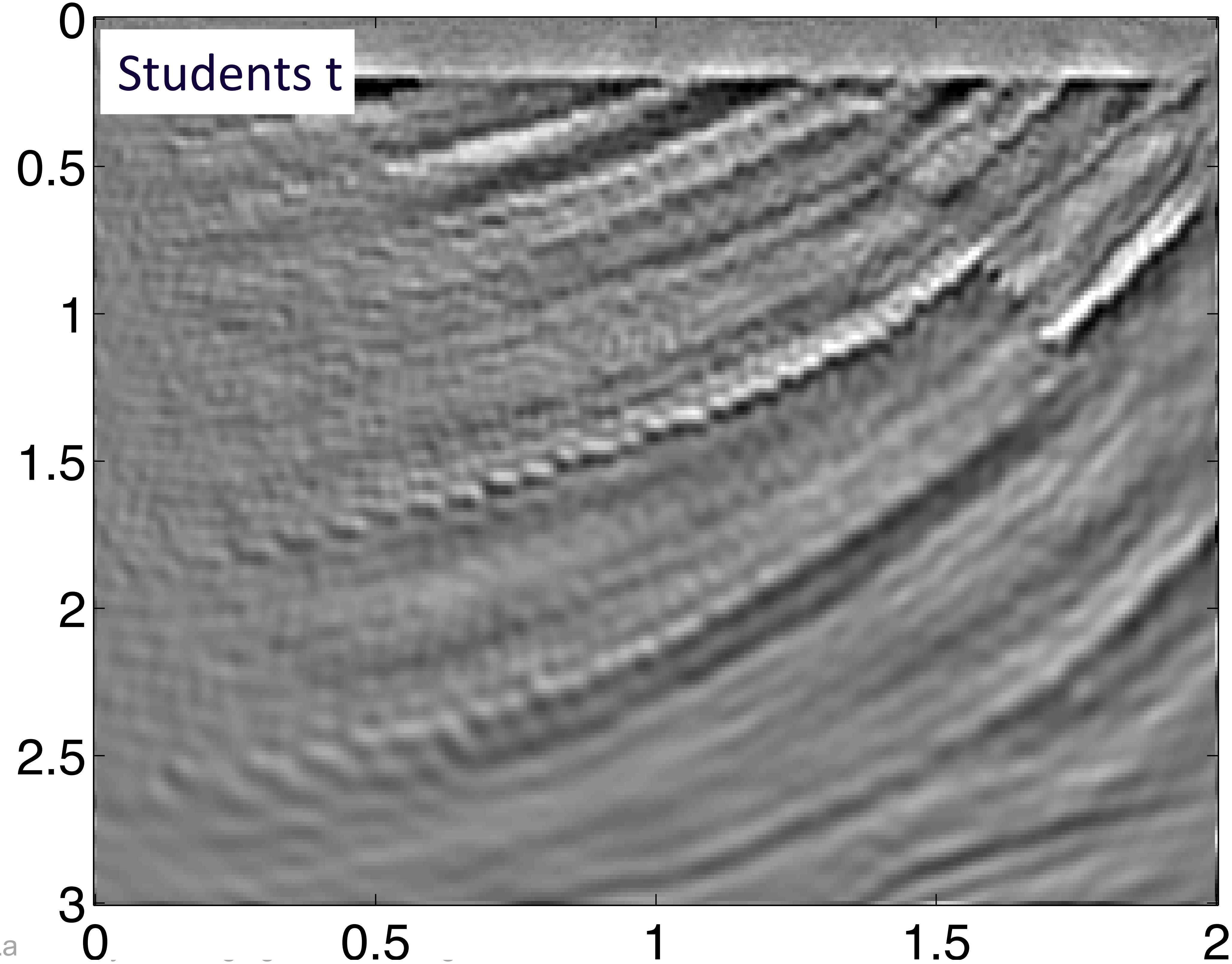
Robust FWI



Robust FWI



Robust FWI

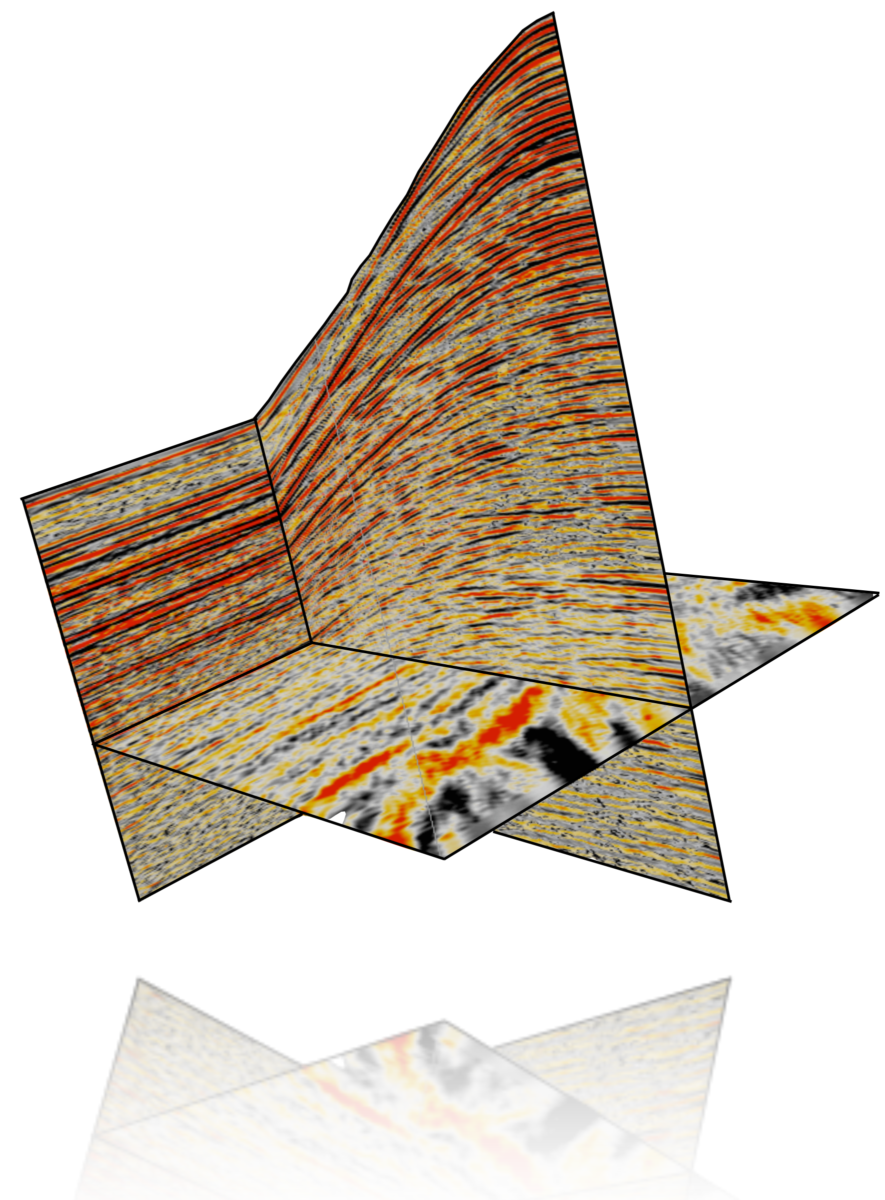


Randomized full-waveform inversion with compressive sensing

Xiang Li, Aleksandr Aravkin, Tristan van Leeuwen, Felix Herrmann. Full-waveform inversion with randomized L1 recovery for the model updates. EAGE 2011, Vienna.

F. J. Herrmann, X. Li, A. Aravkin, and T. van Leeuwen, “A modified, sparsity promoting, Gauss-Newton algorithm for seismic waveform inversion.” Proc. SPIE, vol. 2011, no. 81380V.

Xiang Li and Aleksandr Aravkin and Tristan van Leeuwen and Felix J. Herrmann. TR-2011-12. Fast randomized full-waveform inversion with compressive sensing.



Key contributions

Randomized dimensionality *reduction* (including *marine*)

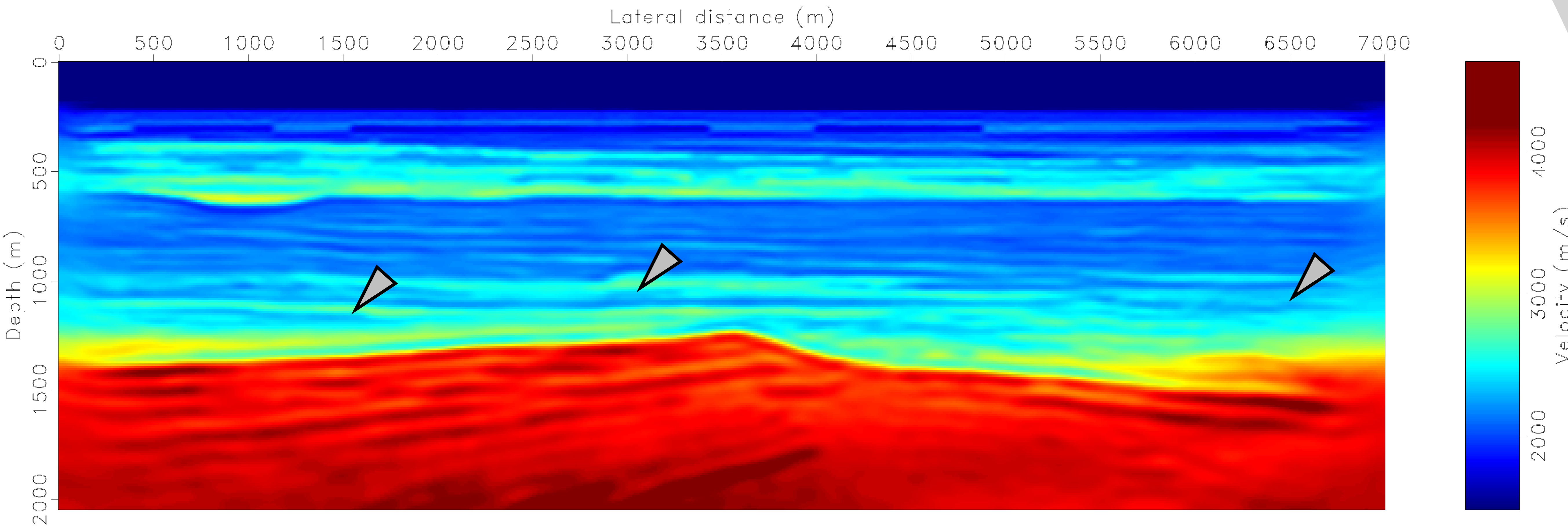
- remove interferences/artifacts by sparsity promotion on the updates
- control over error by renewals and mini batch size

Opportunities

- *adaptive* growing of the mini batch size
- implementation in 3D FWI

Results

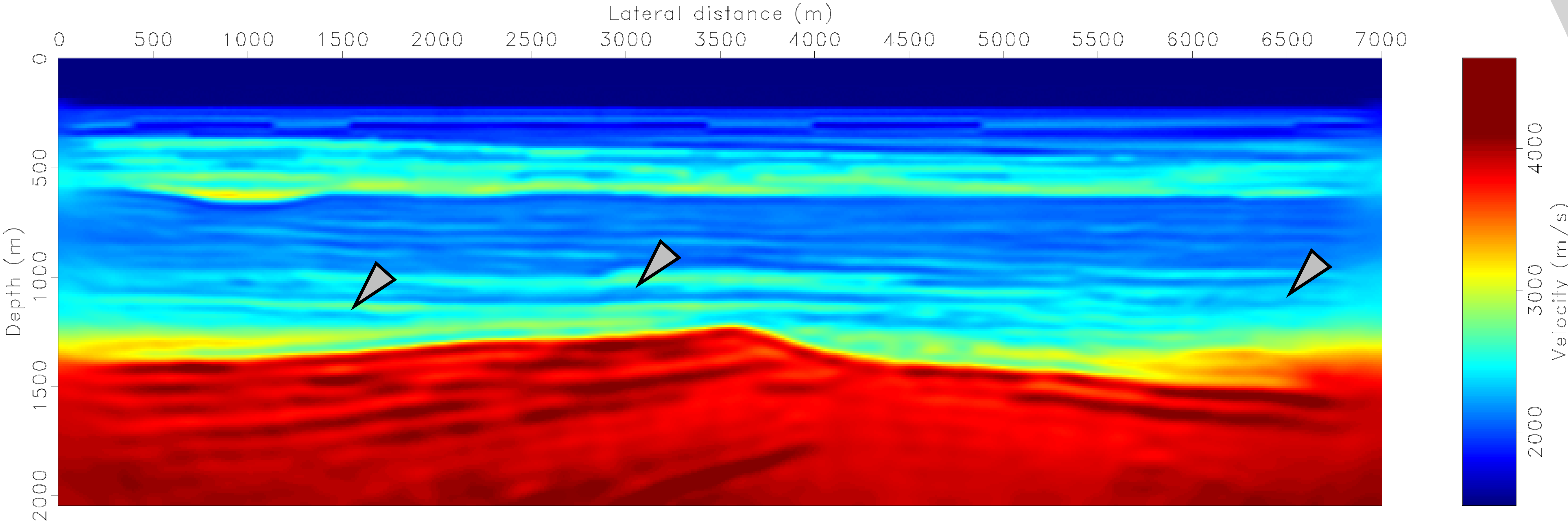
Modified GN 7 seq. shots *with renewals*



25 times speedup compared to full GN

Results

Modified GN 7 sim. shots *with renewals*



25 times speedup compared to full GN

Outcomes

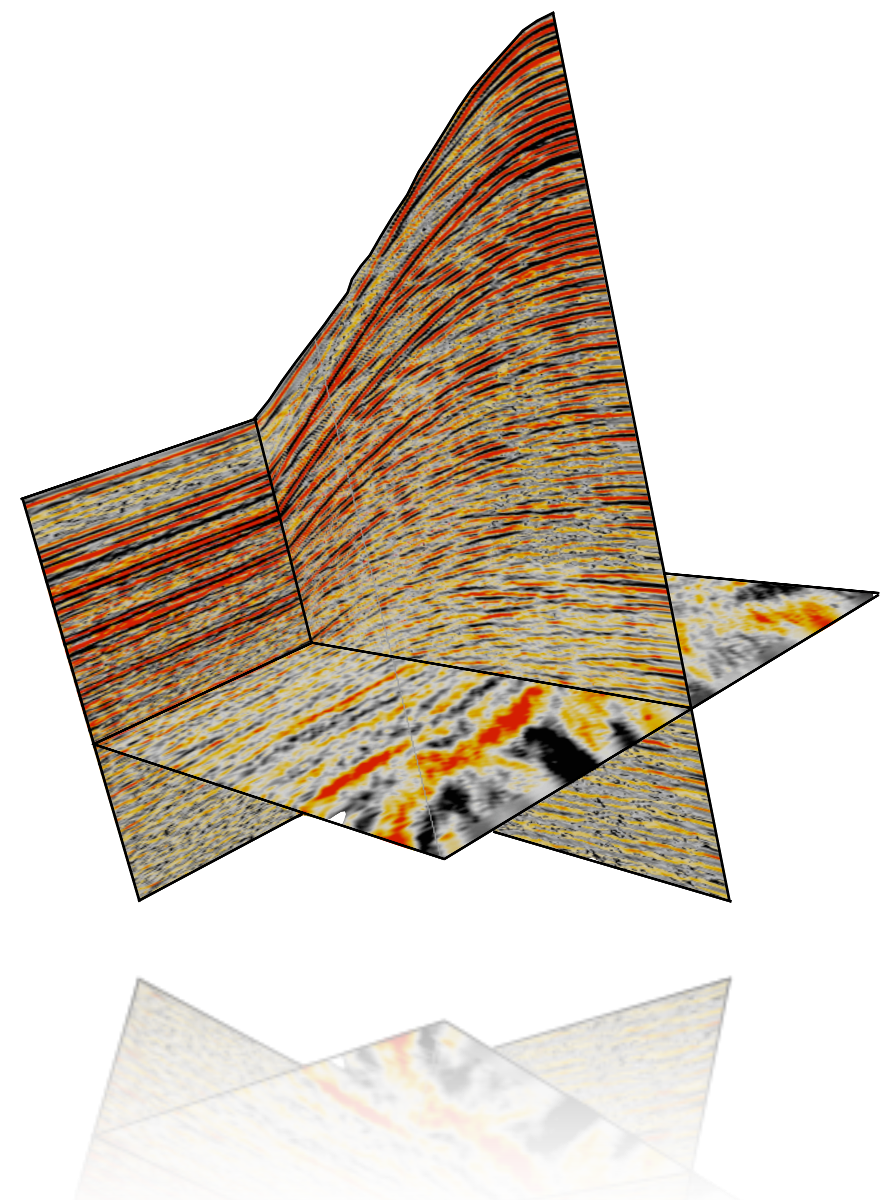
Dimensionality reduced formulation

- based on *mini* batches with *increasing* # of sources
- includes *robustness* for subsets of *sequential* sources
- promotes *sparsity* on GN *updates* from subsets

Uptake by industry

- Student t has been implemented by Total SA

New initiatives



Challenges & opportunities

SLIM's research program is on a roll... but progress is hampered by lack of

- computational facilities to scale to 3D
- warm bodies for growth into a sustainable & more diverse program including
  - rock physics
  - geological context

Initiatives

‘Shale gas’ institute: offering *impartial* scientific advice to government & industry in support of *sustainable* E & P of > 1 *trillion* dollars in reserves of *unconventional* gas in BC

Involves faculty across campus (and beyond) with expertise in

> fractures, non-Newtonian fluids in drilling, hydro geology, geochemistry, reservoir characterization, etc.

Seek financial support for (endowed) faculty & facilities with matching from the province.

Initiatives

‘Brazilian imaging institute’:

- 1 % rule for revenues (Sub/Pre Salt)
- ambitions of Brazil to raise its R & D profile

Unique opportunities

- for collaboration between different research institutes (eg. UBC & Mike Warner from Imperial College)
- shared computational resources to address scale up to 3D
- additional faculty & professional MSc program

Bottom line

Great opportunities to leverage our interdisciplinary research program but to succeed we need commitment from industry that can be leveraged with the Canadian government and UBC.

Our reliance of fossil fuels continues to increase.

These are tough economic times so the climate at UBC is conducive towards this sort of initiatives

- guarantee innovations & exciting research
- next-generation of geoscientists