Recovery of seismic data: practical considerations

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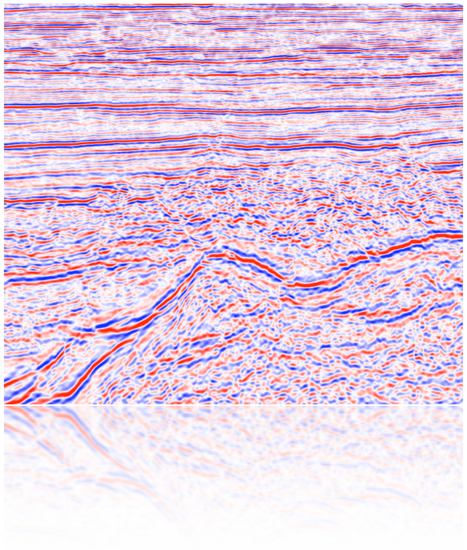


SINBAD meeting: Seismic data regularization
August 28, 2006

Motivation

- improve
  - multiple prediction and removal
  - aliased ground roll removal
  - imaging

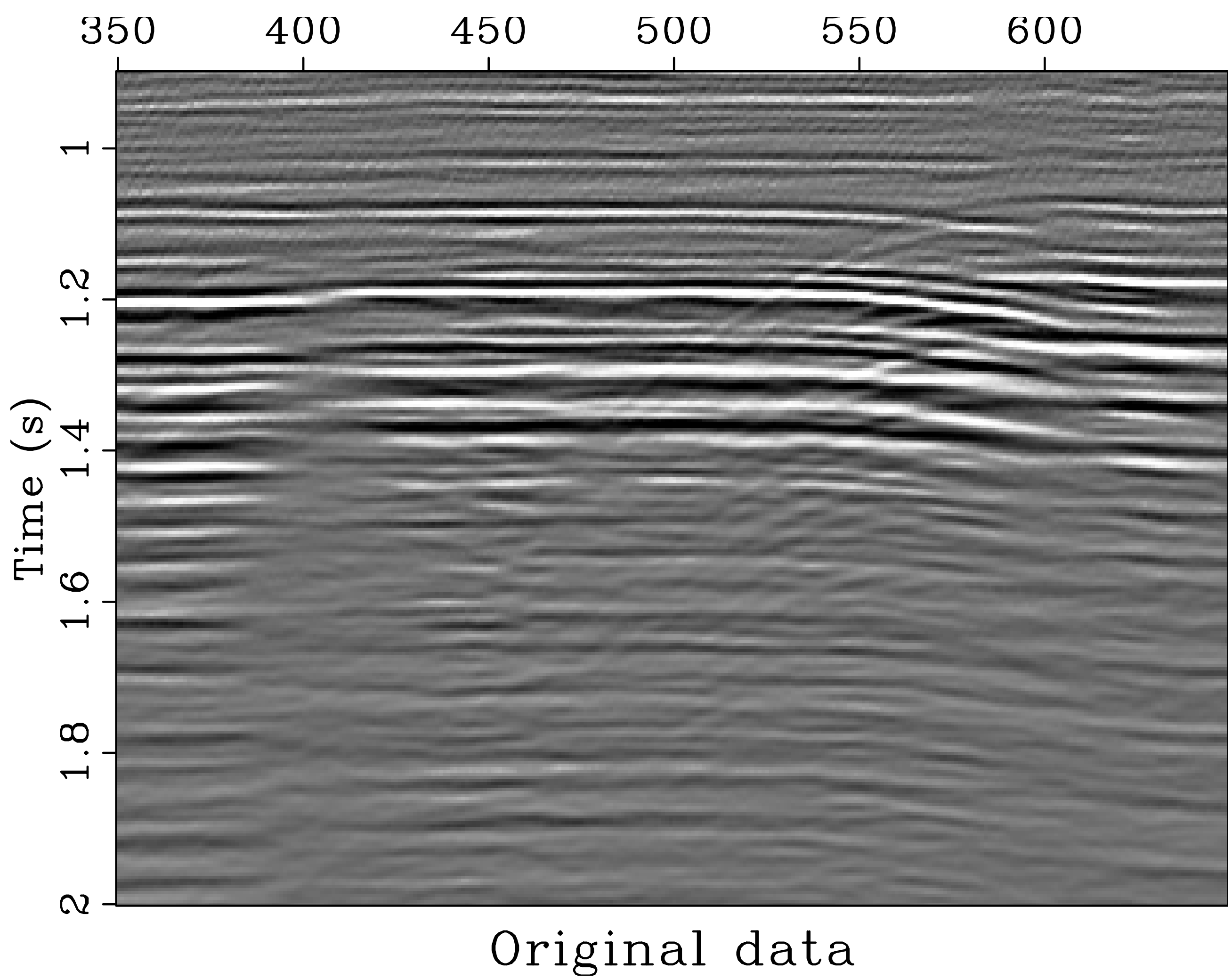
- reduce acquisition cost & time
  - acquire less data

Approach

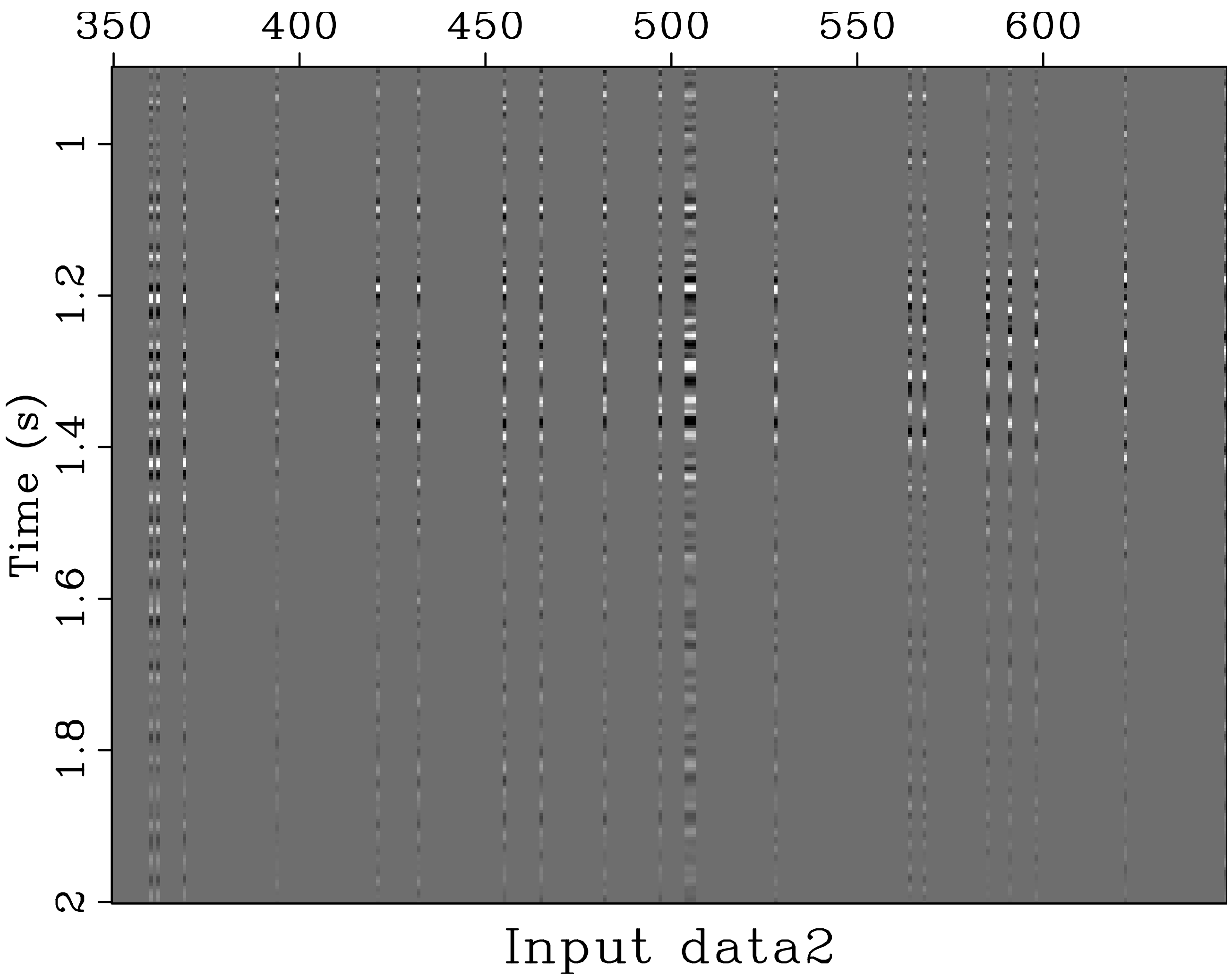
- look at seismic data in a **geometrically correct** way
  - high dimensional
    - typically 5D - i.e. time × source location × receiver location
  - very strong geometrical structure (i.e. wavefronts)

- give **robust sampling criteria** for seismic data
  - interpolation
  - sparse sampling

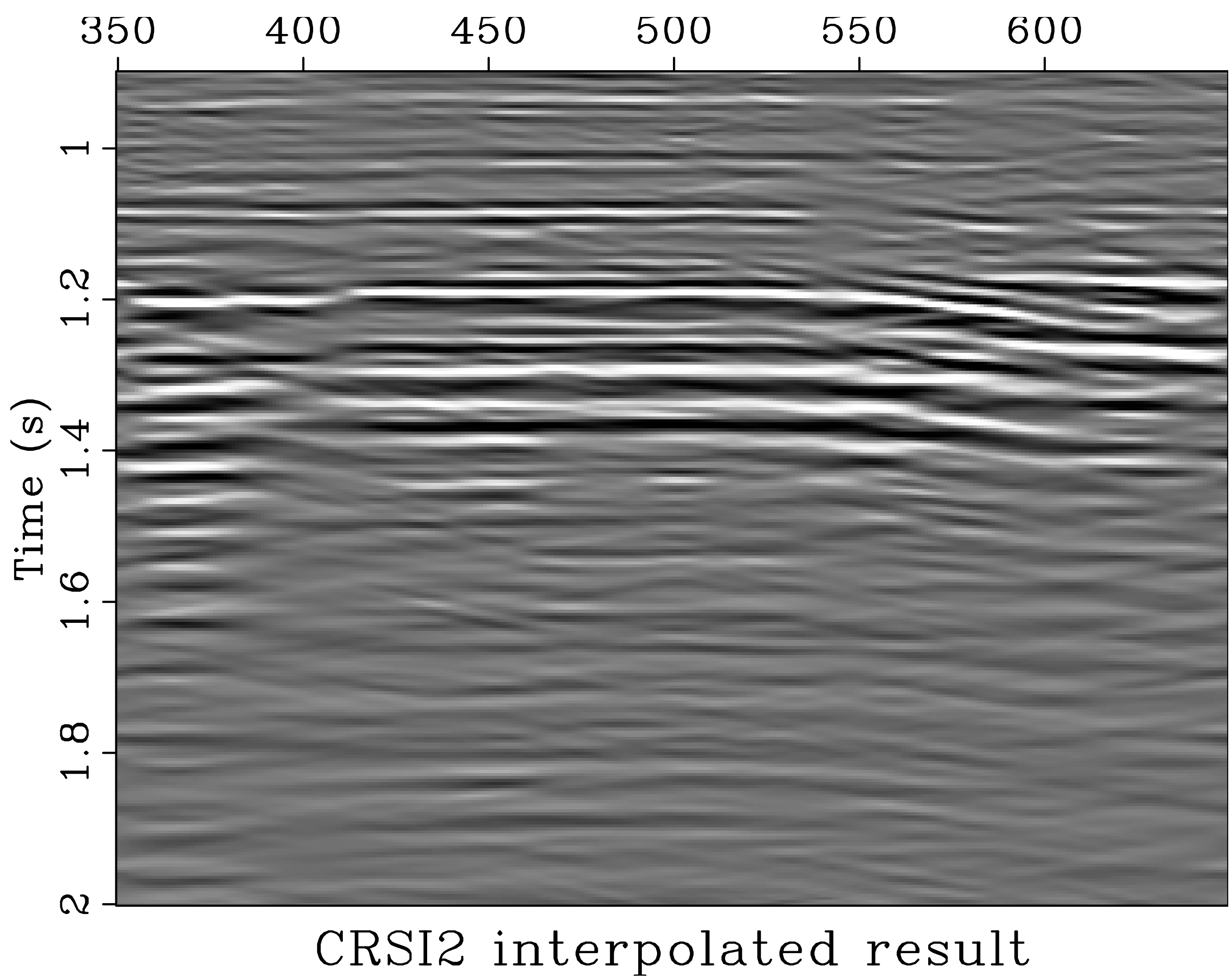
Spatial sampling: 12.5 m



Spatial sampling: avg. 180 m

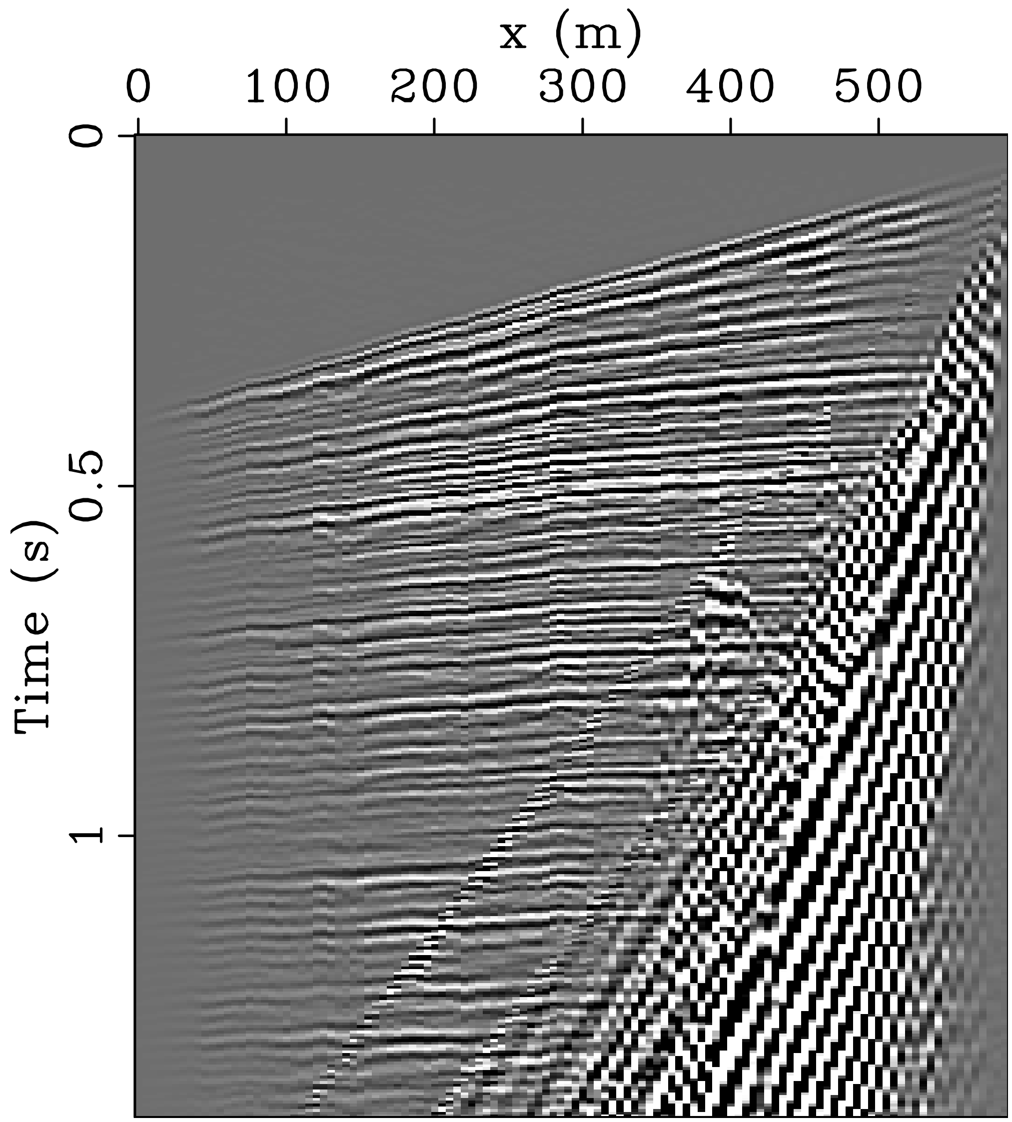


From avg. 180 m to 12.5 m



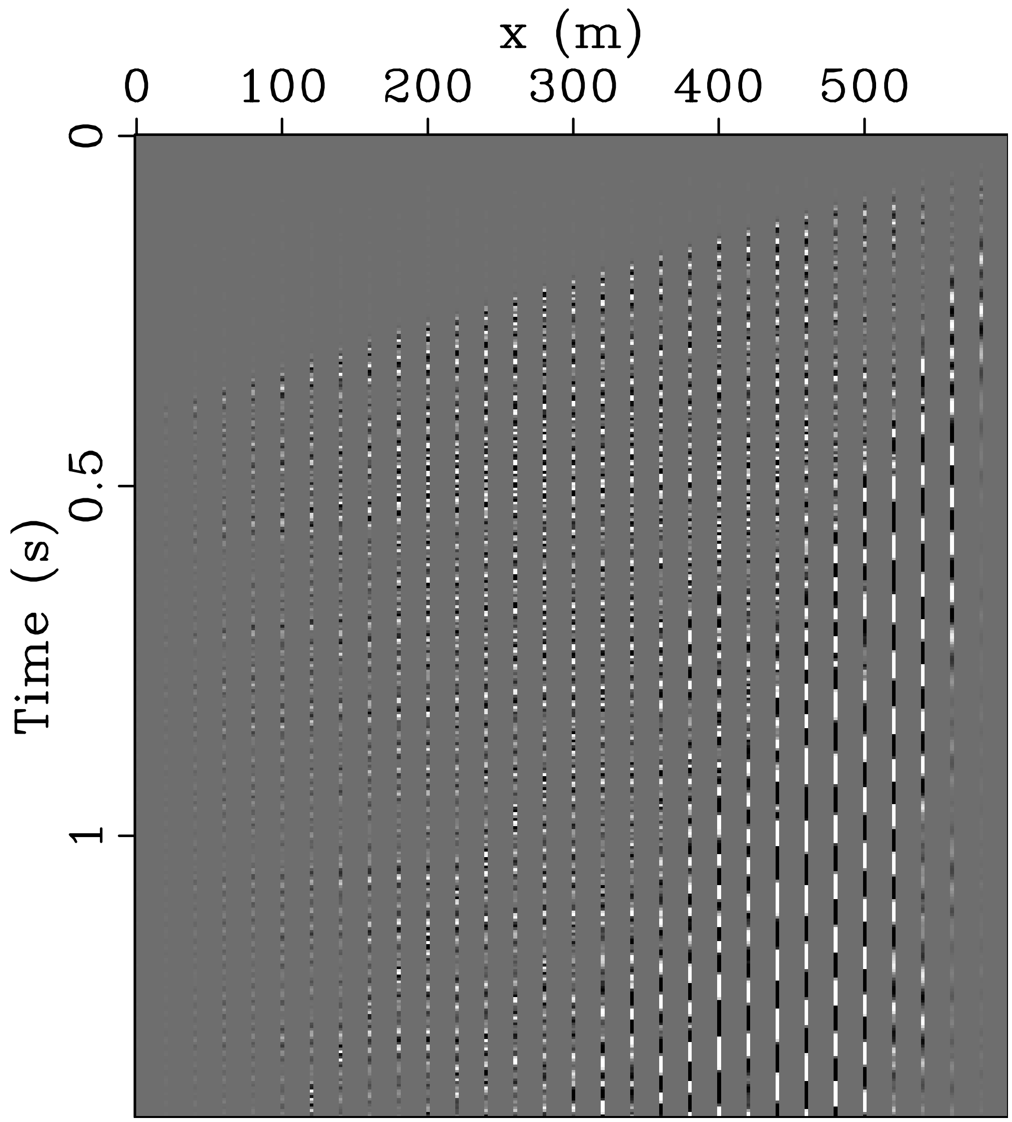
reproducible figure(s)*

Spatial sampling: 5 m



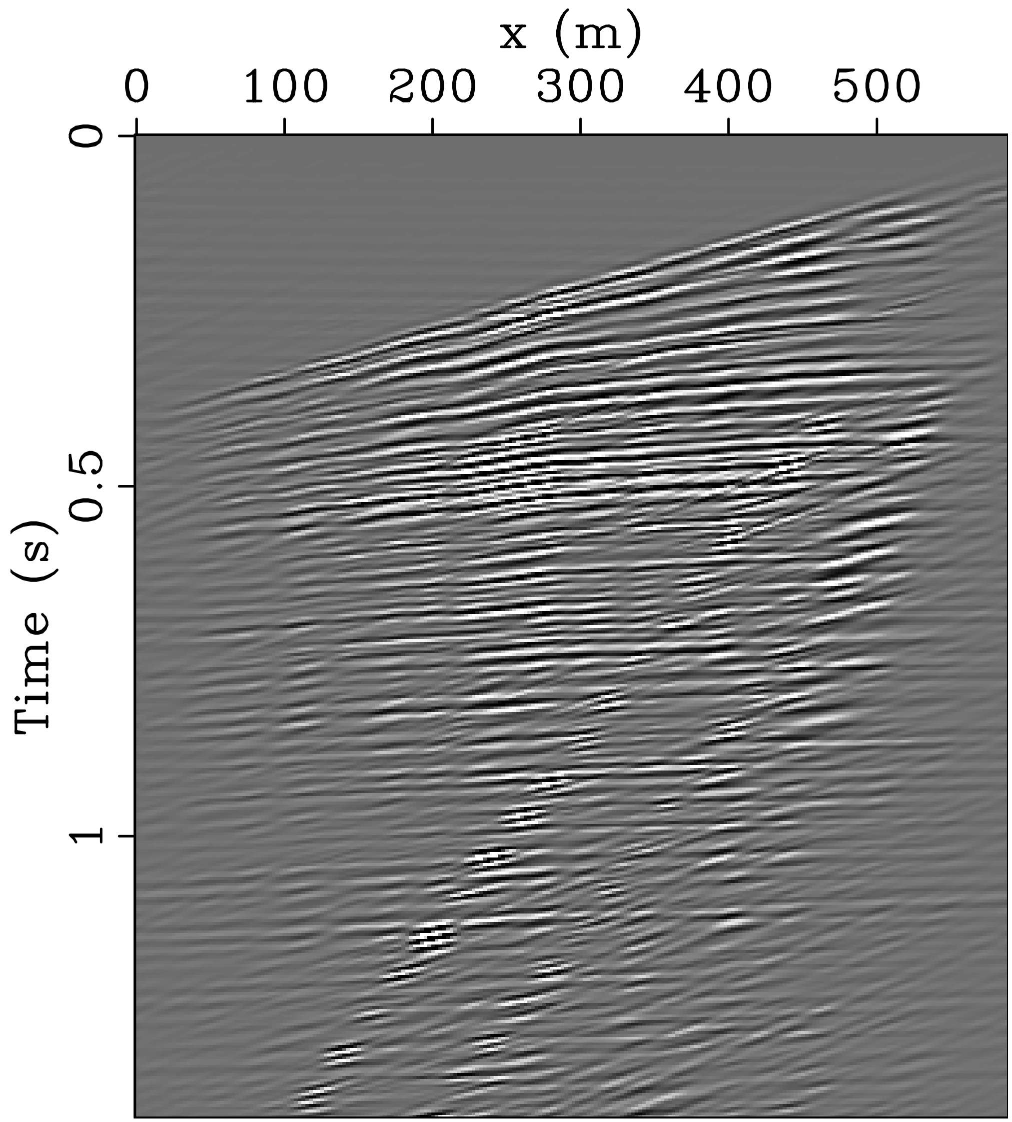
reproducible figure(s)*

Spatial sampling: avg. 20 m



reproducible figure(s)*

From avg. 20 m to 2.5 m



Agenda

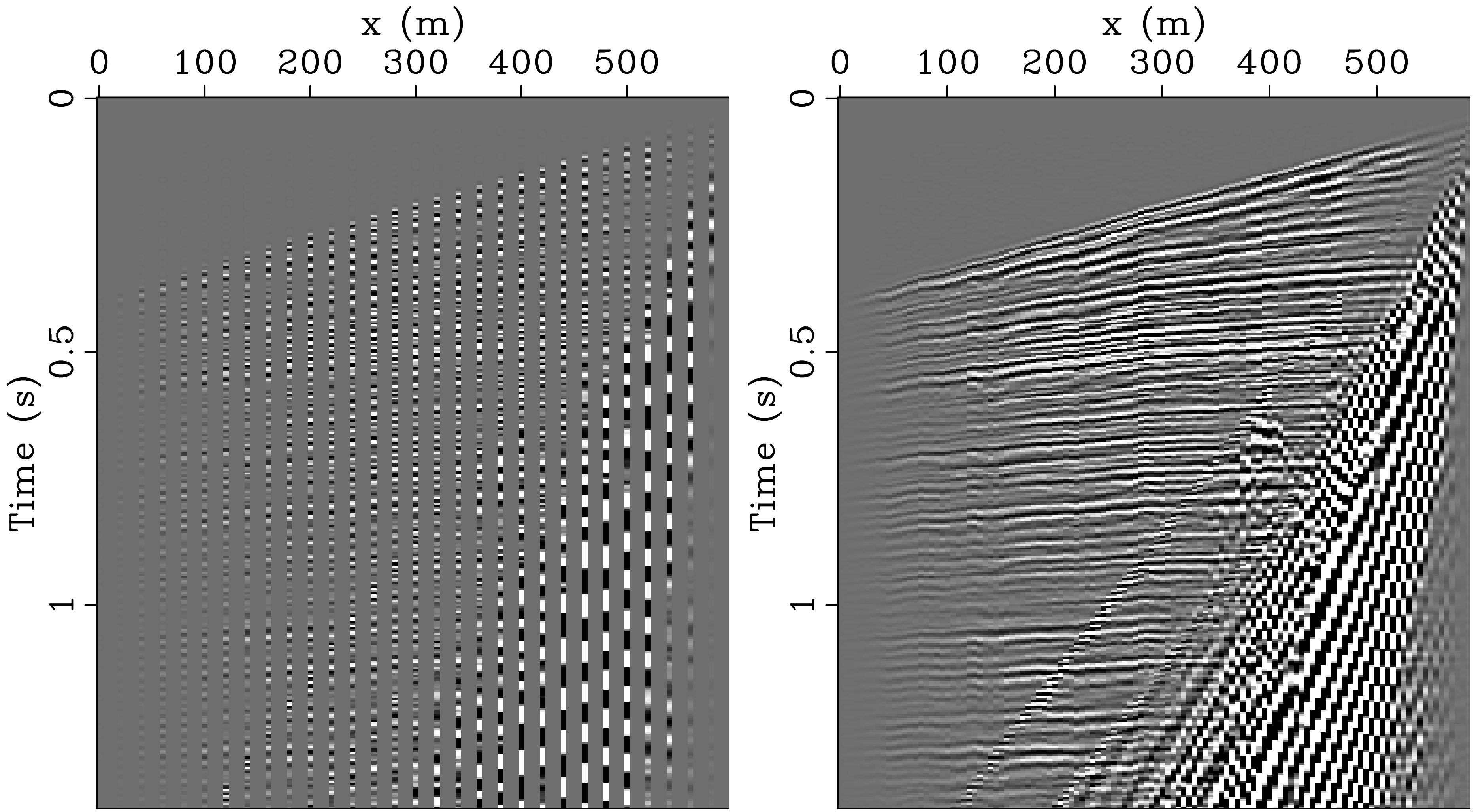
- seismic data interpolation problem
  - "classical" and Curvelet Reconstruction with Sparse Inversion (CRSI) approaches
  - connection between CRSI and stable signal recovery (SSR) theory

- sampling & aliasing
  - is there an "optimal" way of sampling seismic data?

- synthetic and real data examples
  - comparison between CRSI and other interpolation methods available in Madagascar & Fourier Reconstruction with Sparse Inversion (FRSI) by P. Zwartjes
  - uplift from 2D to 3D

reproducible figure(s)*

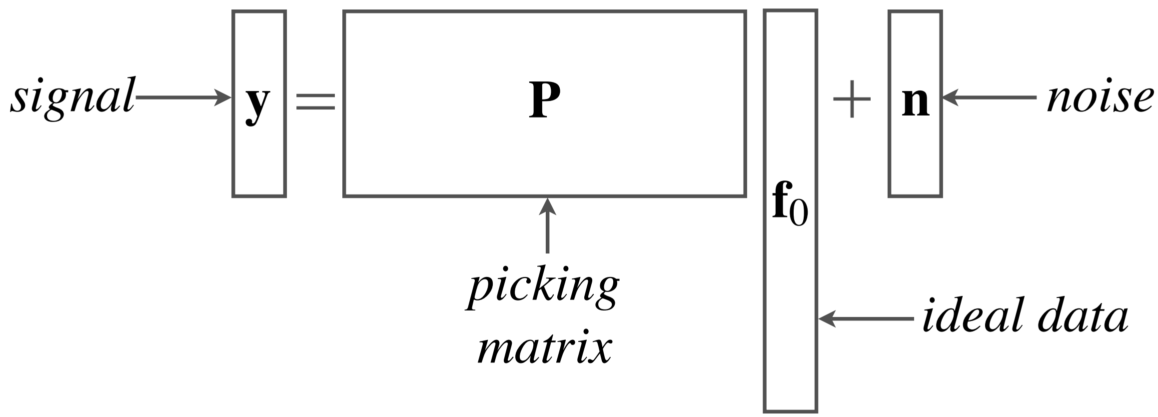
Seismic data interpolation problem



acquired data *ideal data*

Forward and “classical” inverse problem

- (severely) underdetermined system of linear equations
  - infinitely many solutions



- classical approaches
  - minimize energy (i.e. quadratic constraint)

$$\tilde{\mathbf{f}} = \arg\min_{\mathbf{f}} \frac{1}{2} \underbrace{\|\mathbf{y} - \mathbf{P}\mathbf{f}\|_2^2}_{\text{data misfit}} + \lambda \underbrace{\|\mathbf{L}\mathbf{f}\|_2^2}_{\text{energy constraint}}$$

Sparsity-promoting inversion

- reformulation of the problem

signal → $\mathbf{y} = \mathbf{P}\mathbf{C}^H \mathbf{x}_0 + \mathbf{n}$ ← *noise*

$\mathbf{x}_0$ ← *curvelet representation of ideal data*

- severely underdetermined system of linear equations
  - infinitely many solutions
  - want the **sparsest** ← KEY POINT OF THE RECOVERY

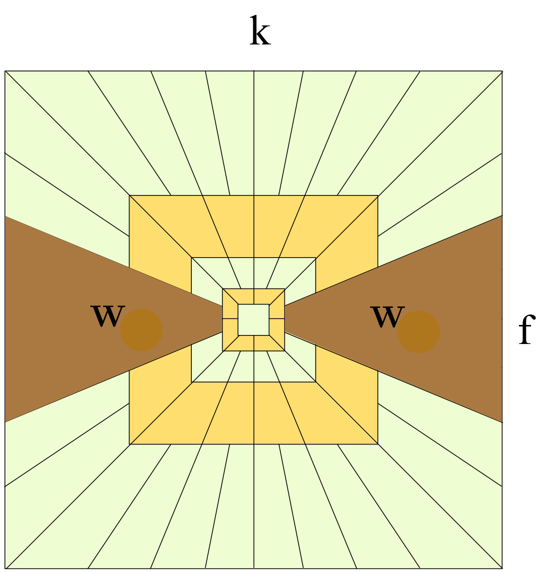
$$(P_0)\begin{cases} \tilde{\mathbf{x}} = \arg\overbrace{\min_{\mathbf{x}} \|\mathbf{x}\|_0}^{\text{sparsity constraint}} \quad \text{s.t.} \quad \overbrace{\|\mathbf{y} - \mathbf{P}\mathbf{C}^H\mathbf{x}\|_2}^{\text{data misfit}} \leq \varepsilon \\ \tilde{\mathbf{f}} = \mathbf{C}^H\tilde{\mathbf{x}} \end{cases}$$

← combinatorial problem (intractable!!)

Just relax...

- CRSI
  - convex problem

$$(P_1)\begin{cases}\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{W}\mathbf{x}\|_1 \quad \text{s.t.} \quad \|\mathbf{y}-\mathbf{P}\mathbf{C}^H\mathbf{x}\|_2 \le \varepsilon \\ \tilde{\mathbf{f}} = \mathbf{C}^H\tilde{\mathbf{x}}\end{cases}$$



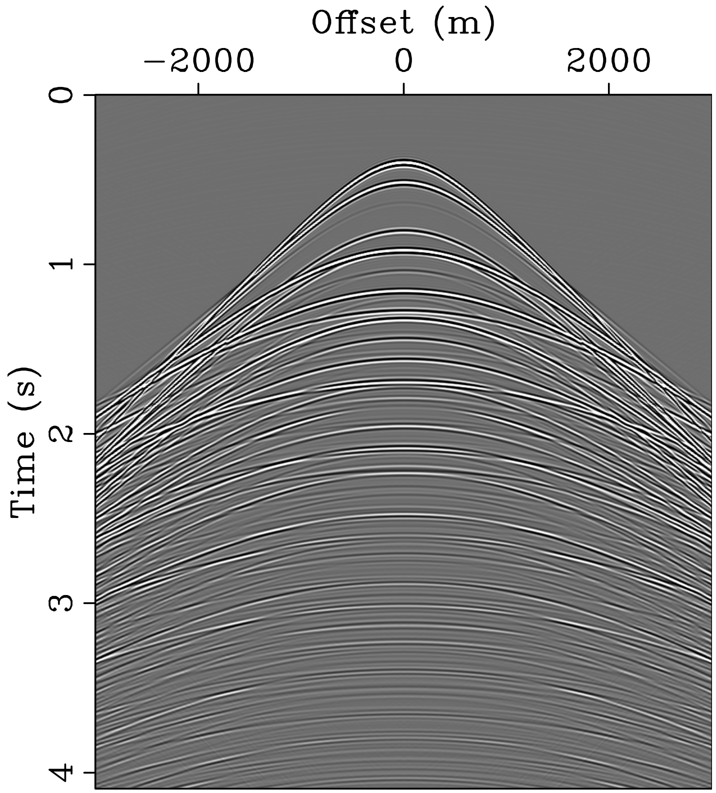
- underpinning SSR theory
  - shows under which circumstances (P_1) solves (P_0)
  - provides a **recovery condition**

Note:

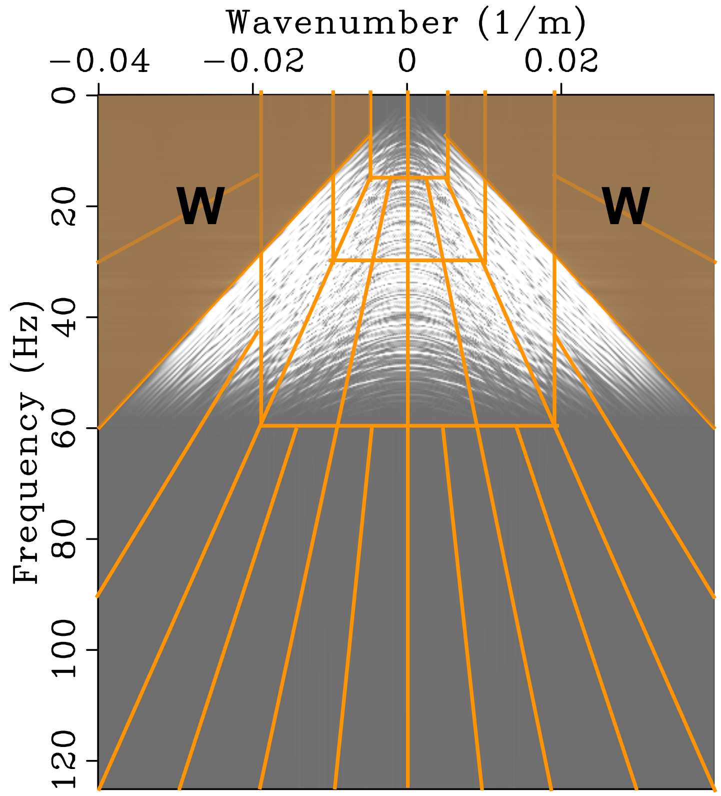
FRSI imposes sparsity in the Fourier domain

Closer look at the curvelet weighting

- **W** (highly) penalizes or removes close to vertical curvelets
  - similar to a minimum velocity constraint



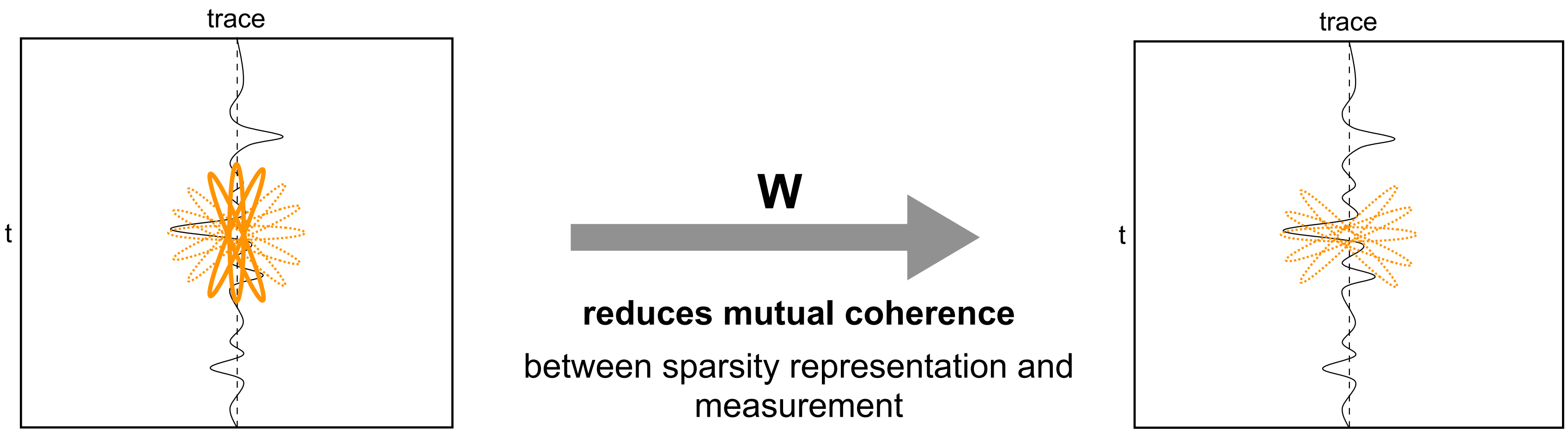
Data



FK

CRSI, FRSI & SSR

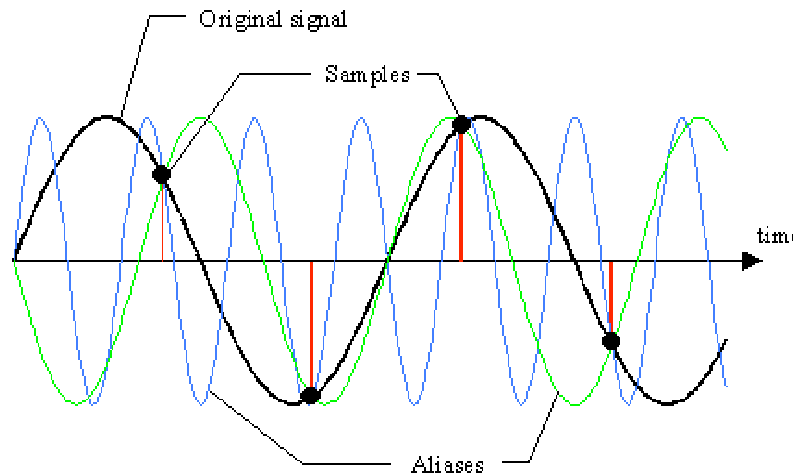
- sparsity representation
  - **curvelets better exploit the very strong geometrical structure** of seismic data than Fourier
- seismic sampling & curvelets



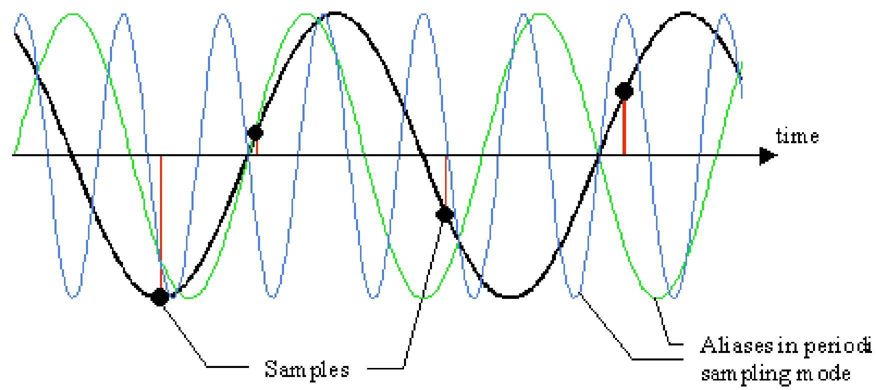
- CRSI thus features a **weighted transform** that
  - offers **sparser representation** for seismic data than Fourier
  - has **low mutual coherence** with seismic sampling comparable with Fourier

Sampling & aliasing

- uniform sampling
  - aliasing problem
  - several sinusoids explain the data



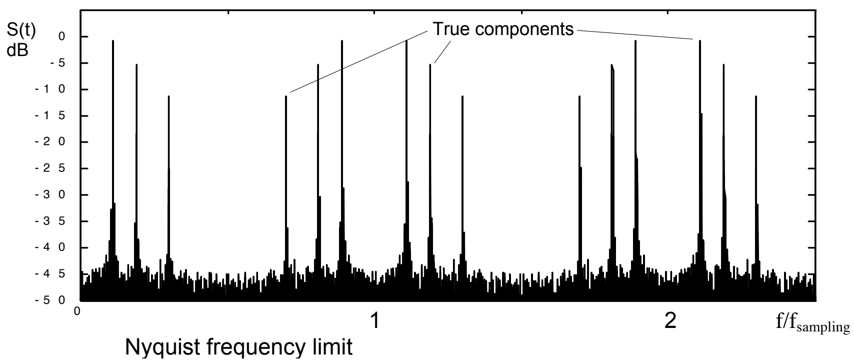
- nonuniform sampling
  - avoid aliasing
  - unique sinusoid explains the data

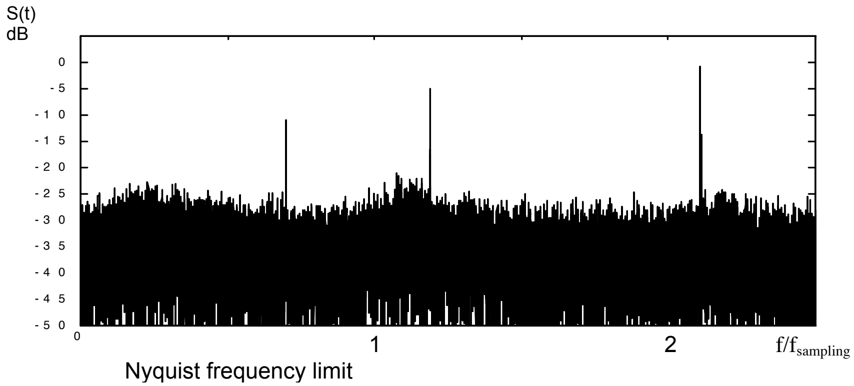


http://www.edi.lv/dasp-web/

From aliasing to noise

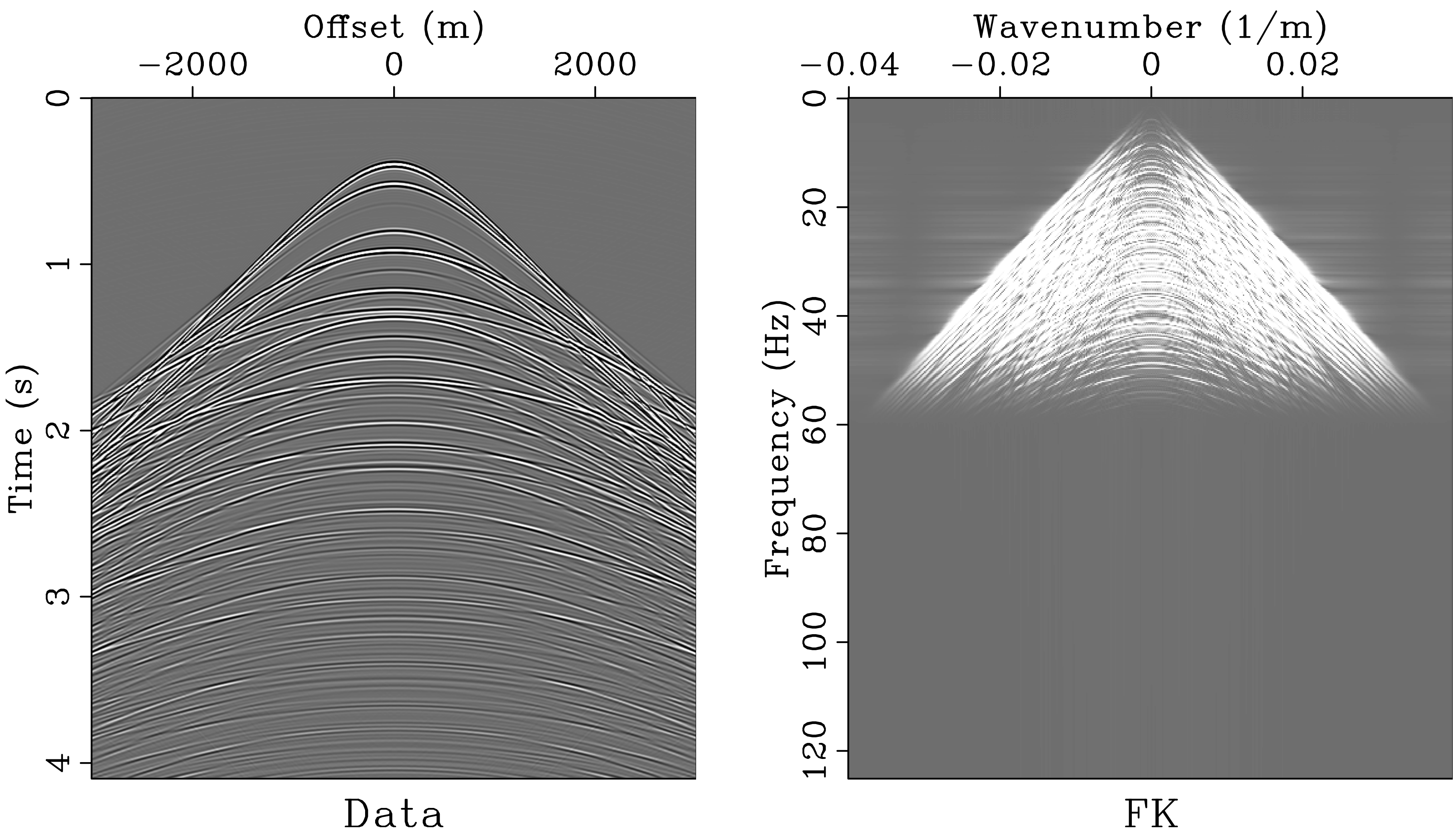
- noisy 1D signal containing three sinusoidal components
  - periodic sampling
    - low noise level
    - aliases for signal components
  - nonuniform sampling
    - noise level higher
    - **no aliases** for signal components



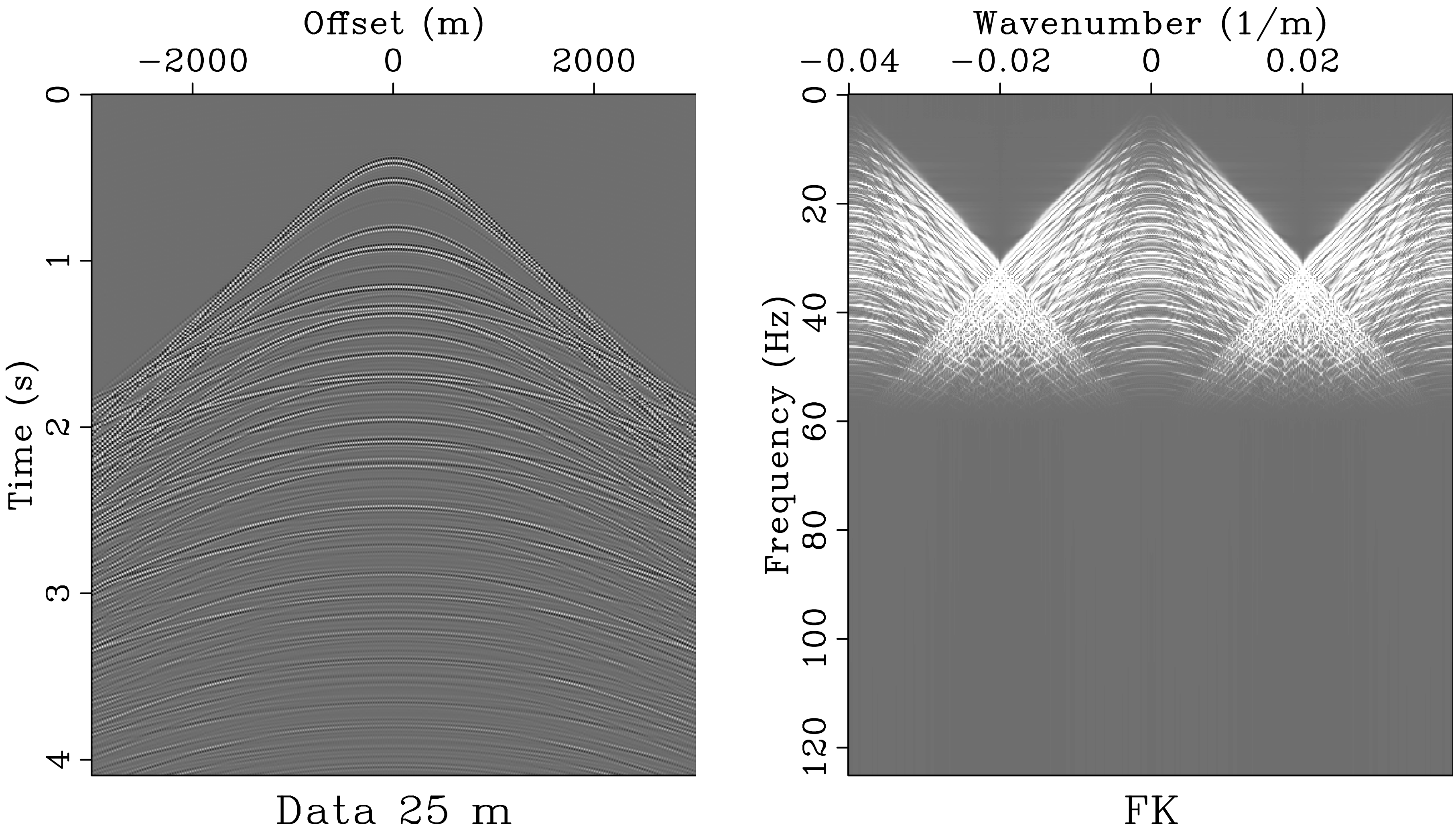


http://www.edi.lv/dasp-web/

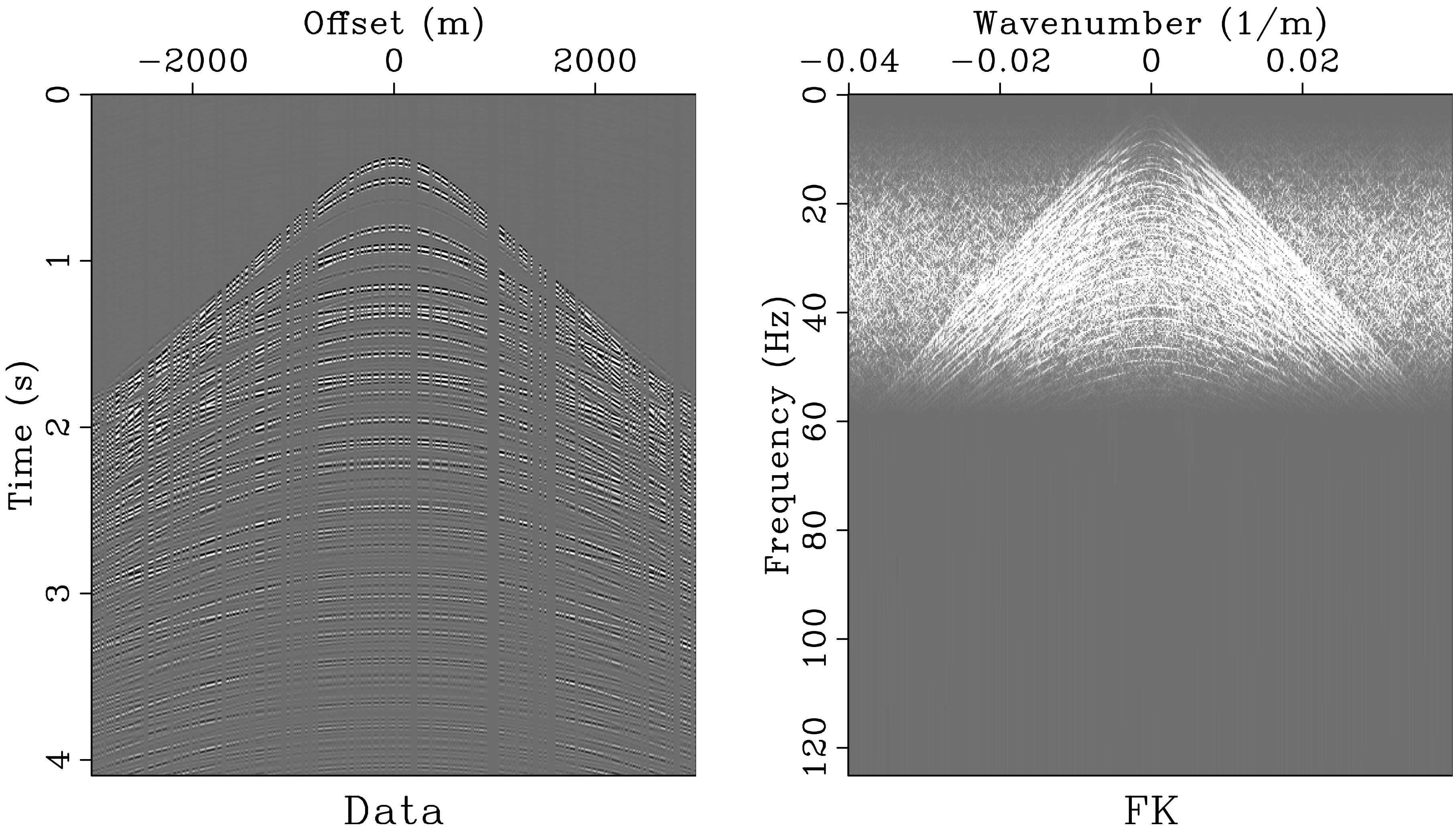
Example: synthetic data (12.5 m)



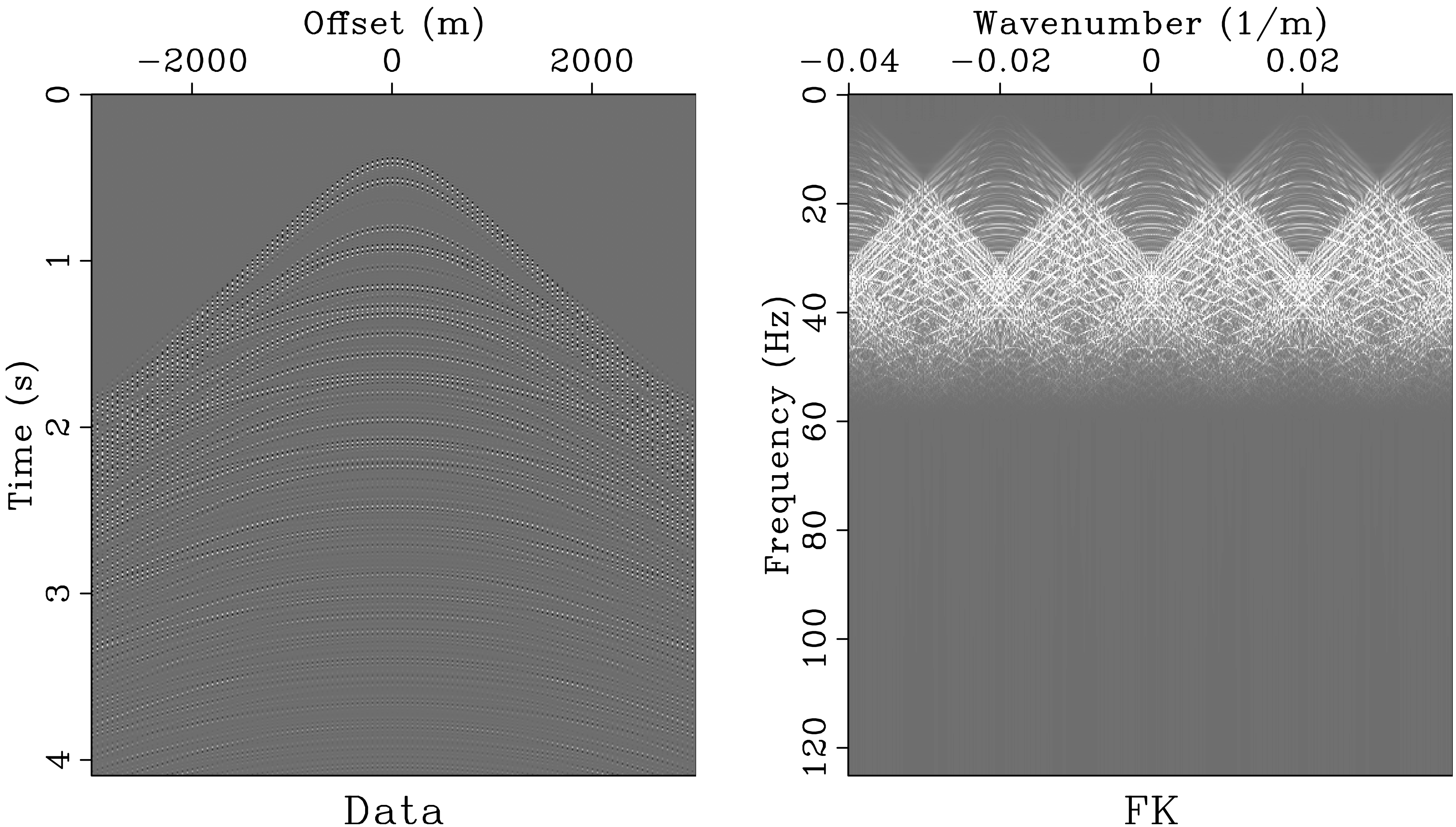
Example: synthetic data (25 m)



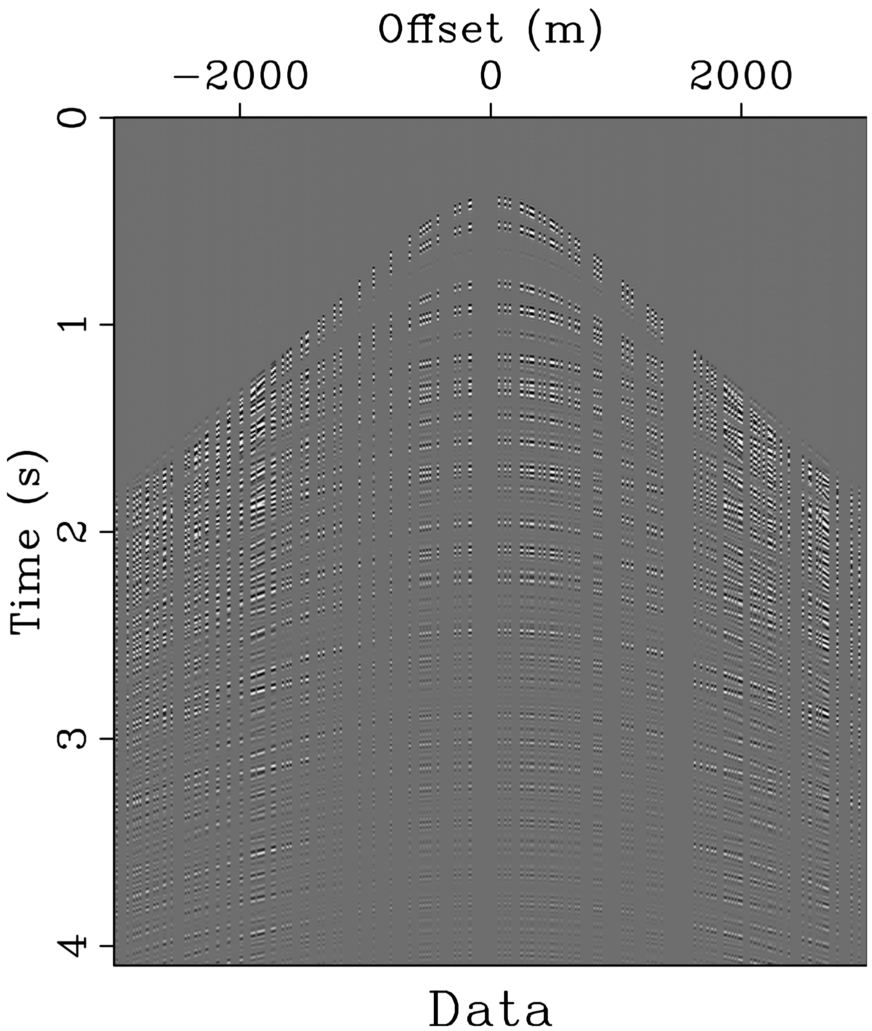
Example: synthetic data (avg. 25 m)

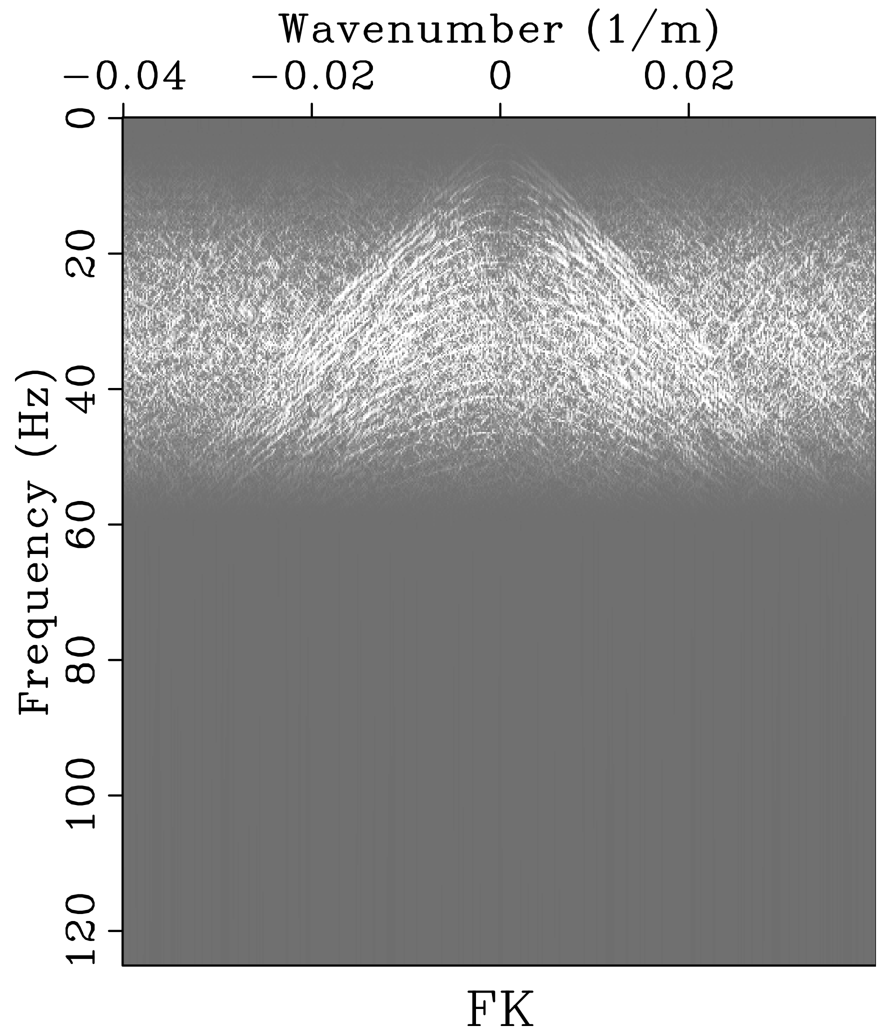


Example: synthetic data (50 m)



Example: synthetic data (avg. 50 m)

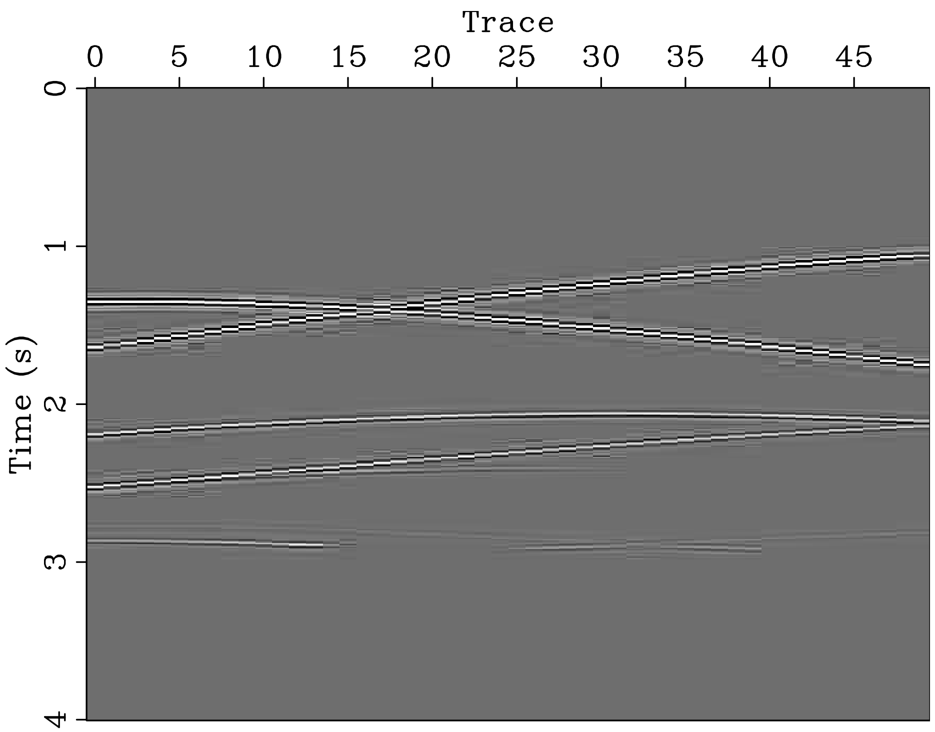




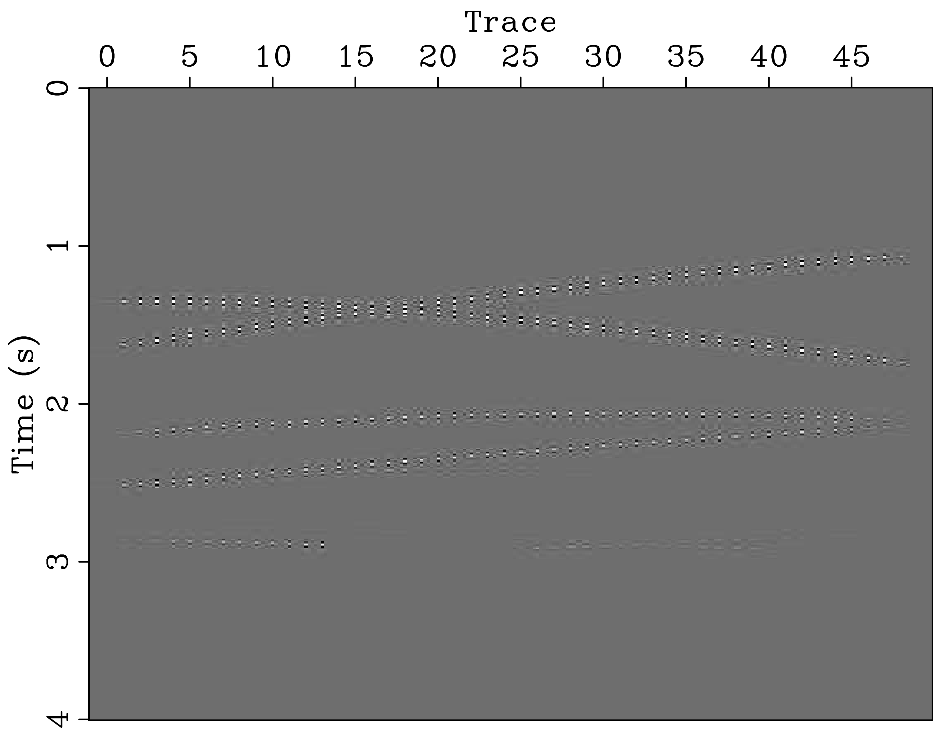
Examples

- synthetic 1: “data from hell” courtesy CWP
  - SLIMpy interpolation “app” demo (tomorrow 2:45 pm)
  - comparison between and other interpolation methods available in Madagascar
- synthetic 2: Delphi’s primary-multiple dataset
  - comparison between CRSI, Plane Wave Destruction (PWD) and FRSI
  - uplift from 2D to 3D (time × source location × receiver location) interpolation
- real 1: Gippsland courtesy ExxonMobil
  - SSE raw stack
  - use SLIMpy interpolation “app”
- real 2: Friendswood courtesy ExxonMobil
  - land data
  - use SLIMpy interpolation “app”

Increasing spatial sampling 1:5

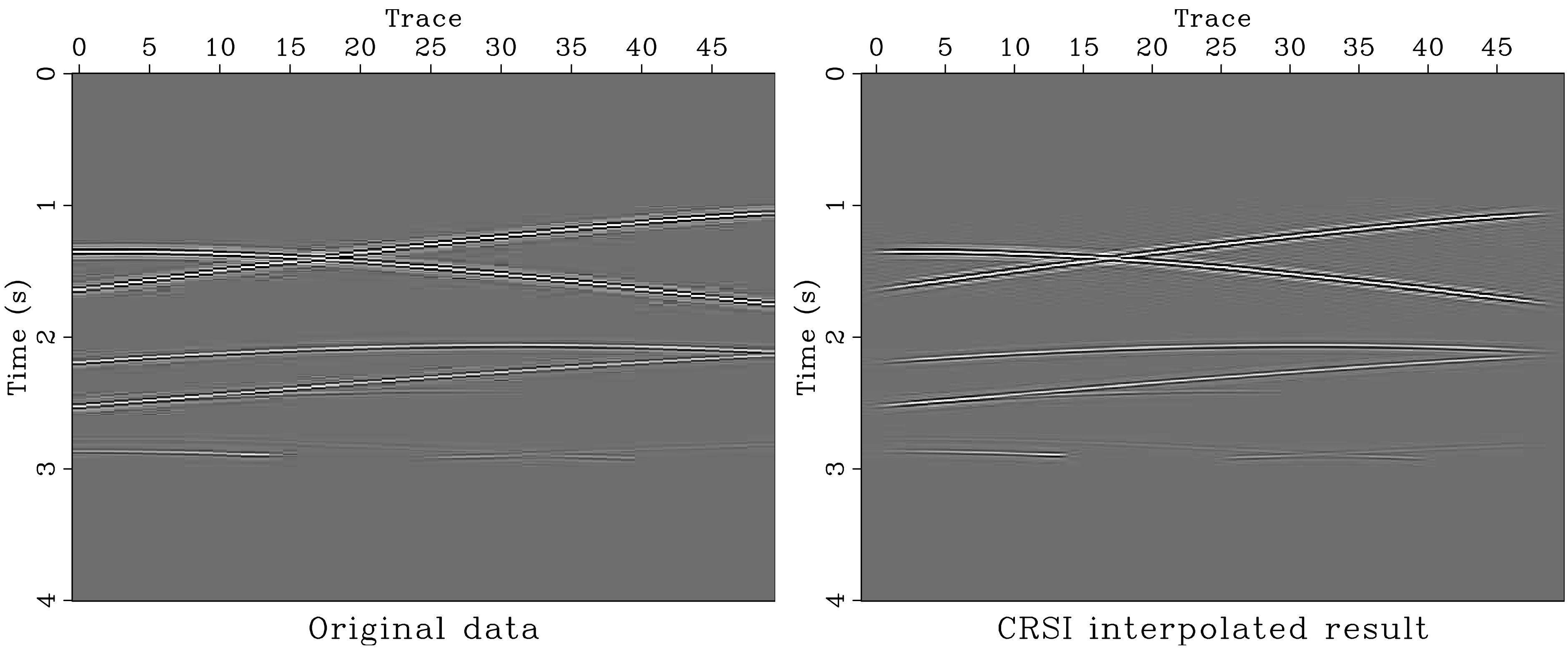


Original data

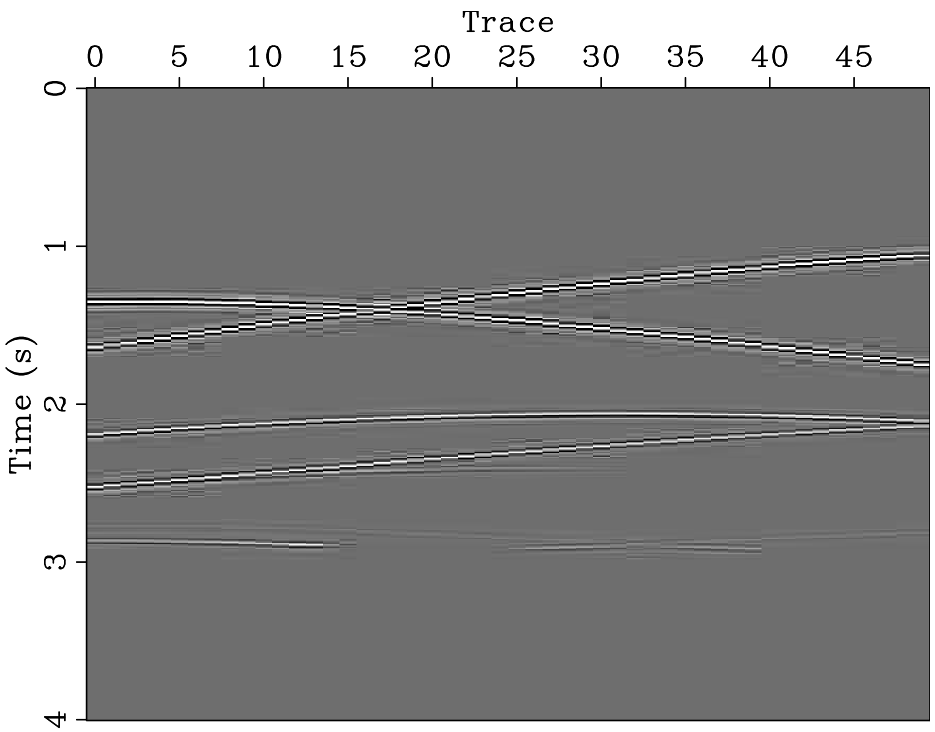


Input data

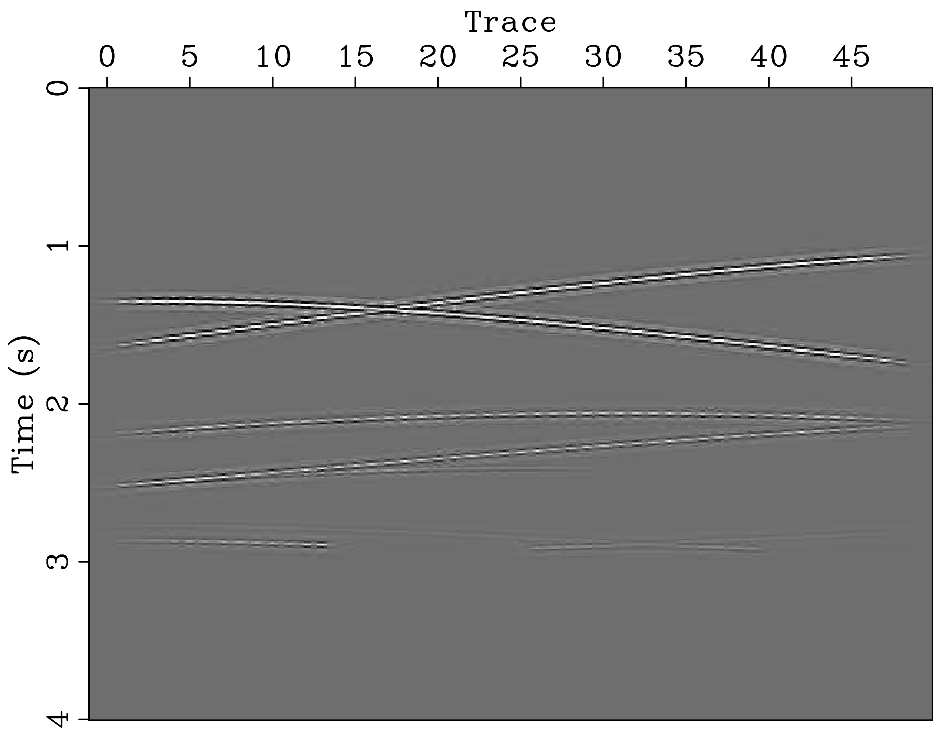
Increasing spatial sampling 1:5



Increasing spatial sampling 1:5

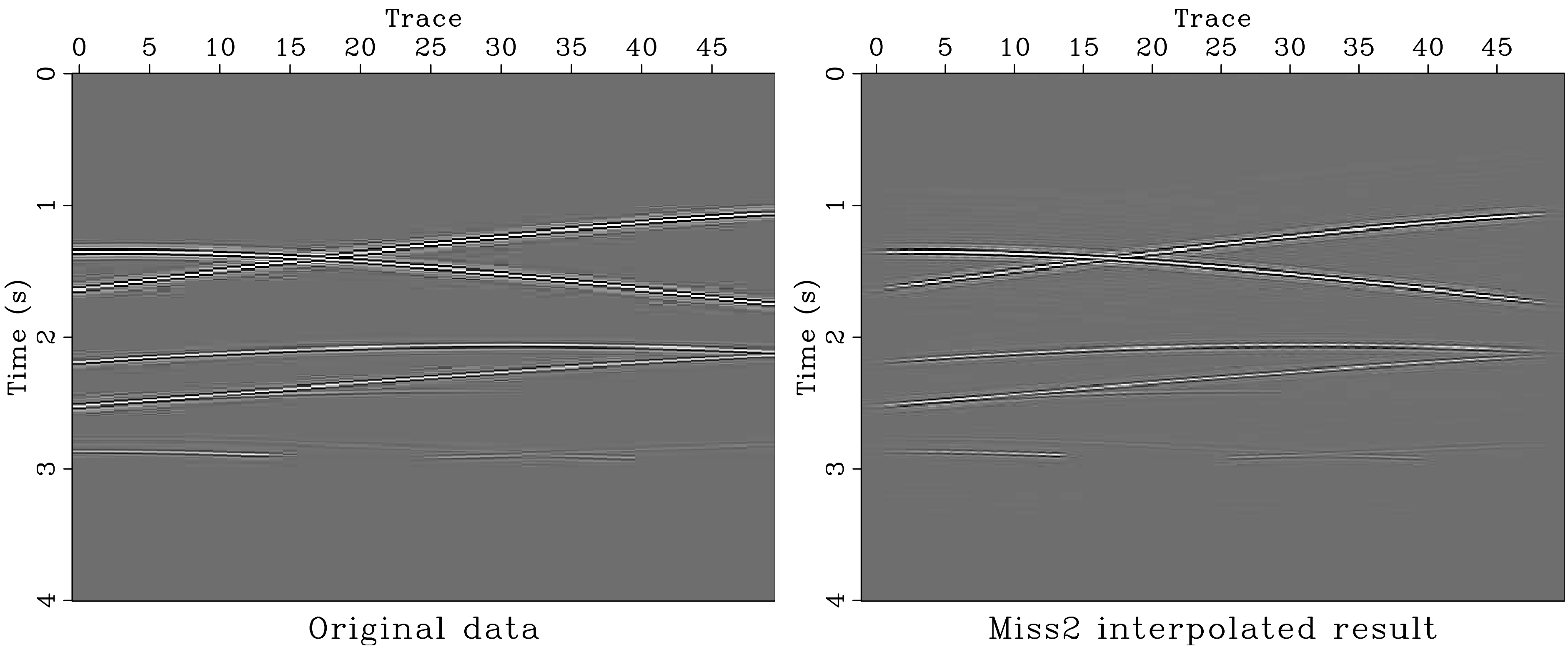


Original data

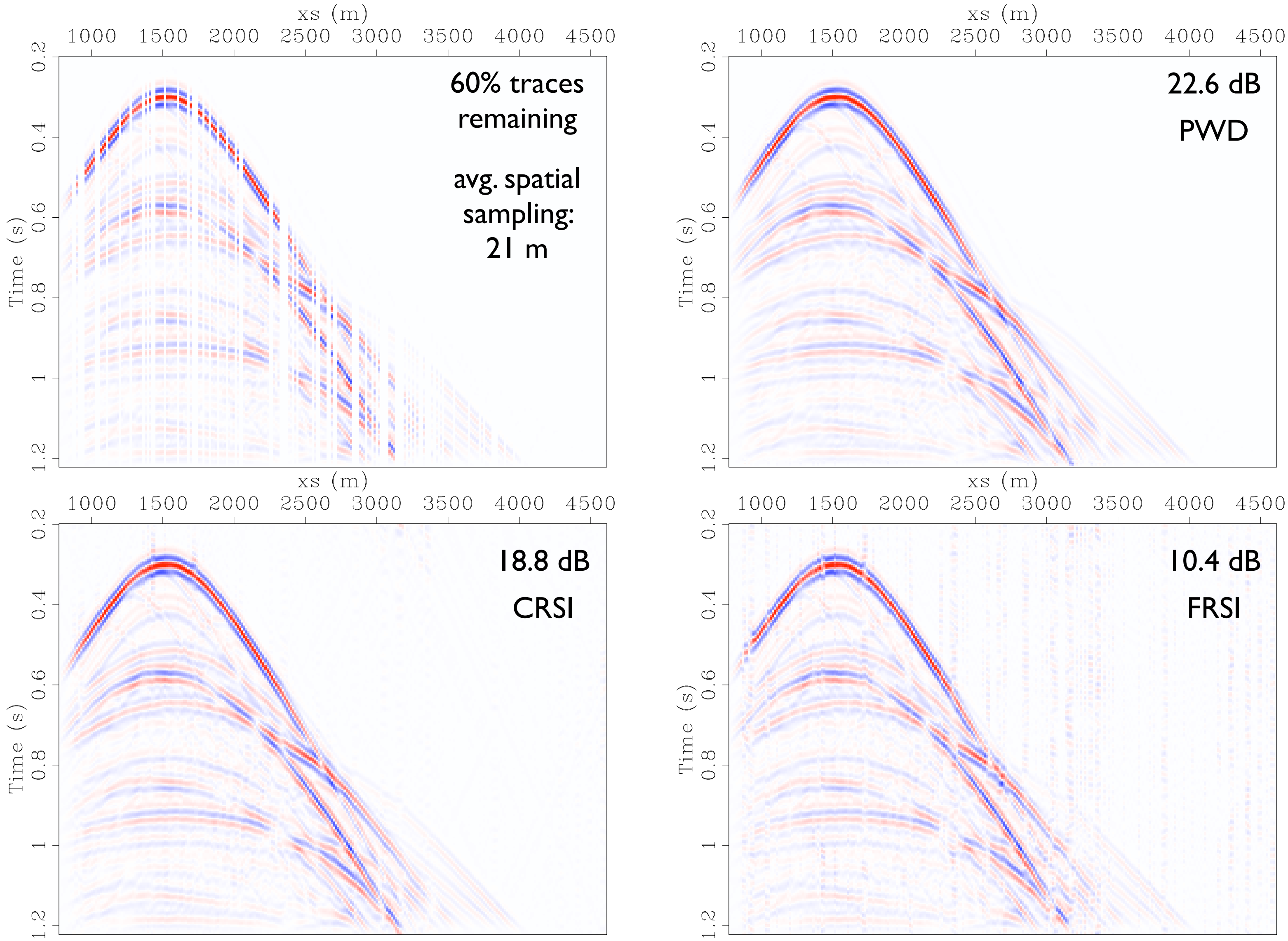


Laplacian reg. interpolated result

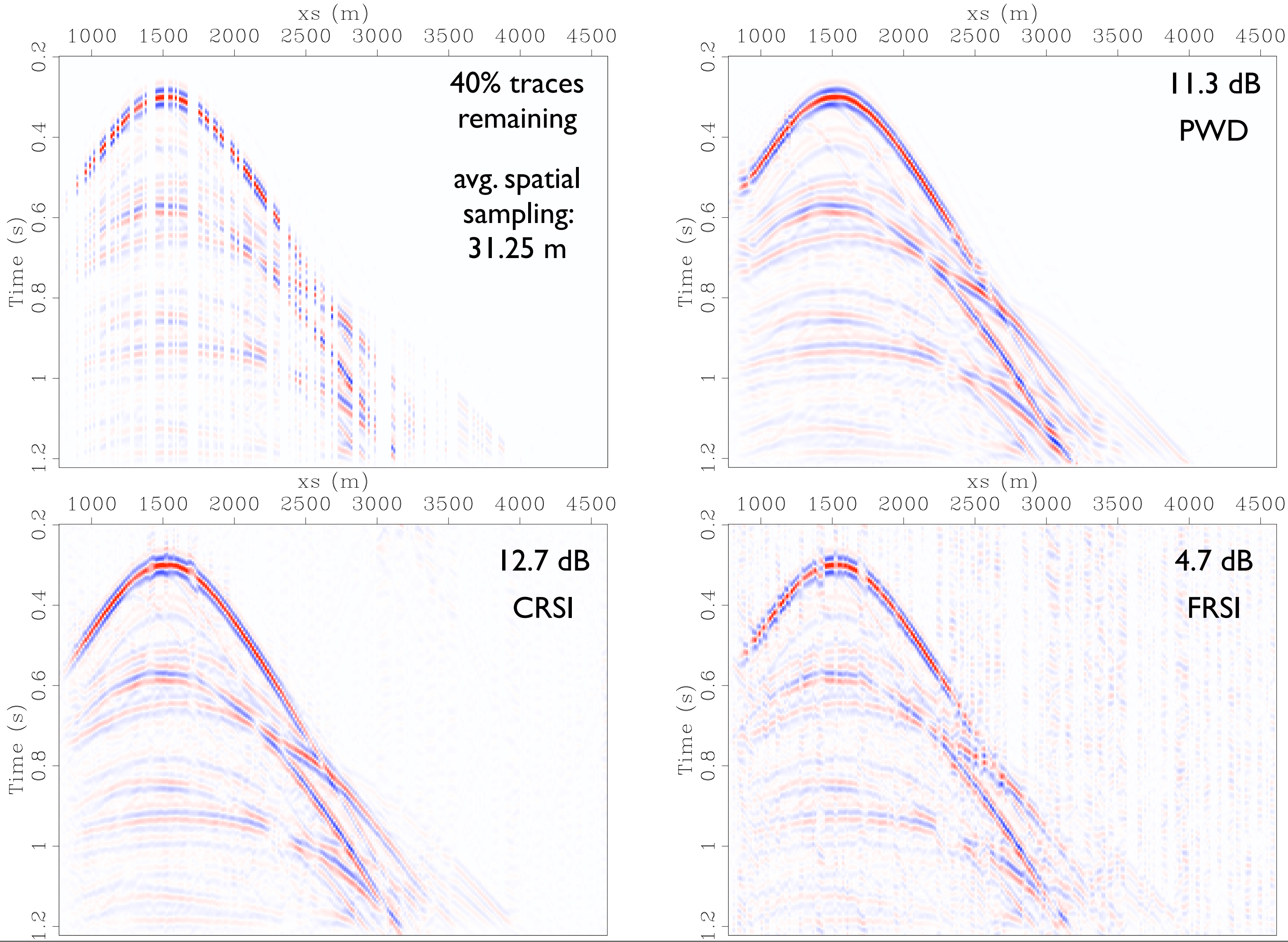
Increasing spatial sampling 1:5



From avg. 21 m to 12.5 m

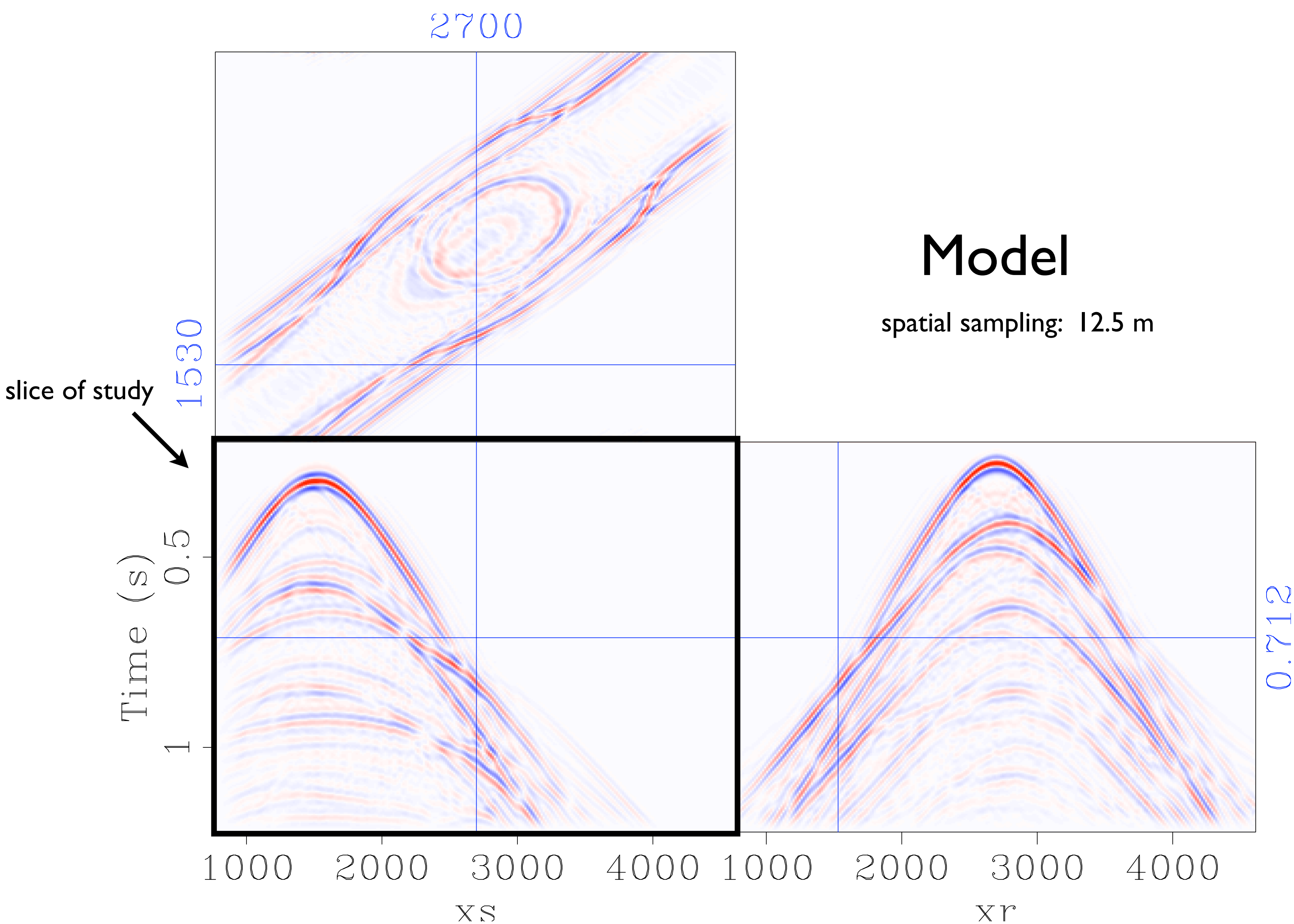


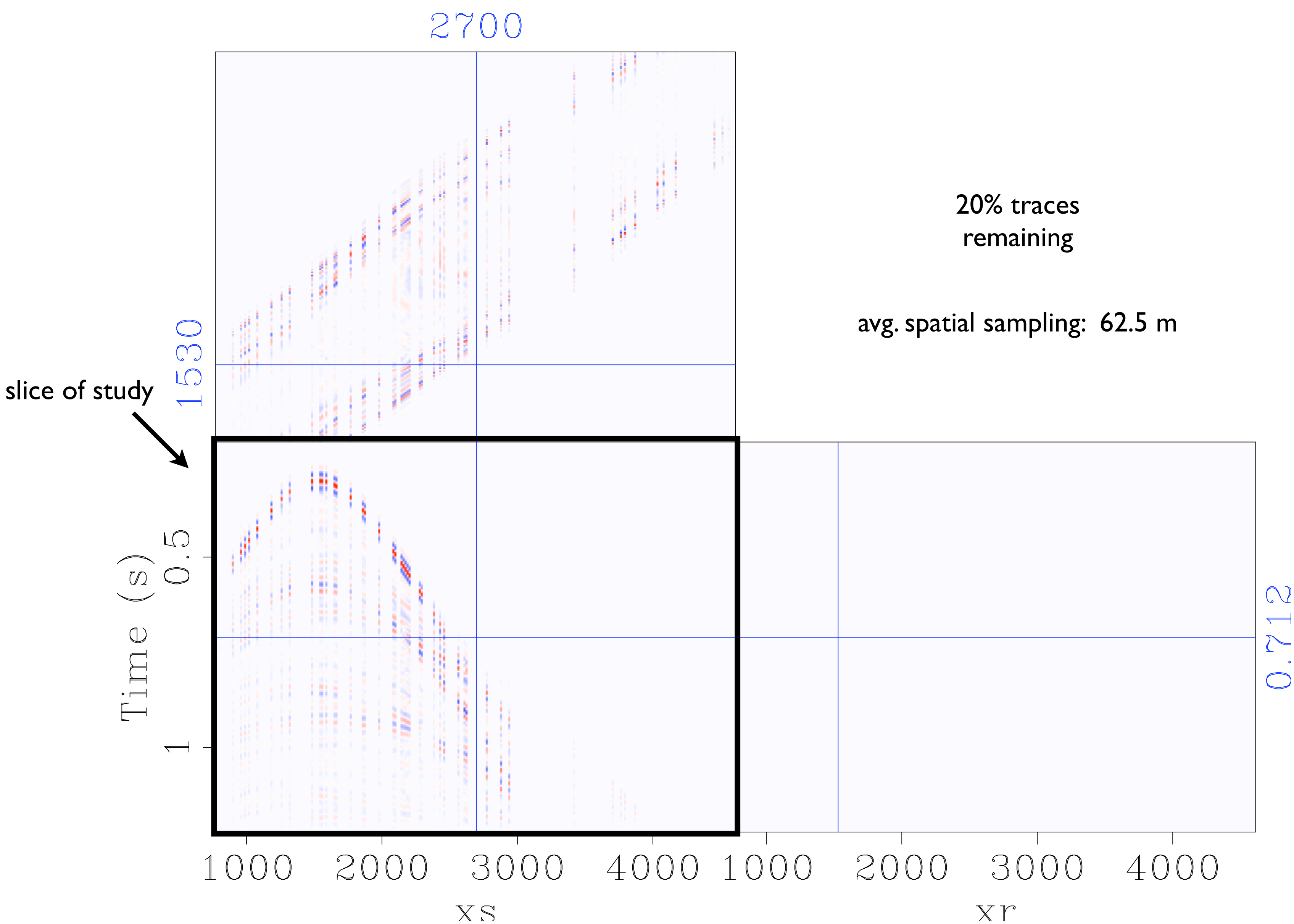
From avg. 31.25 m to 12.5 m



Model

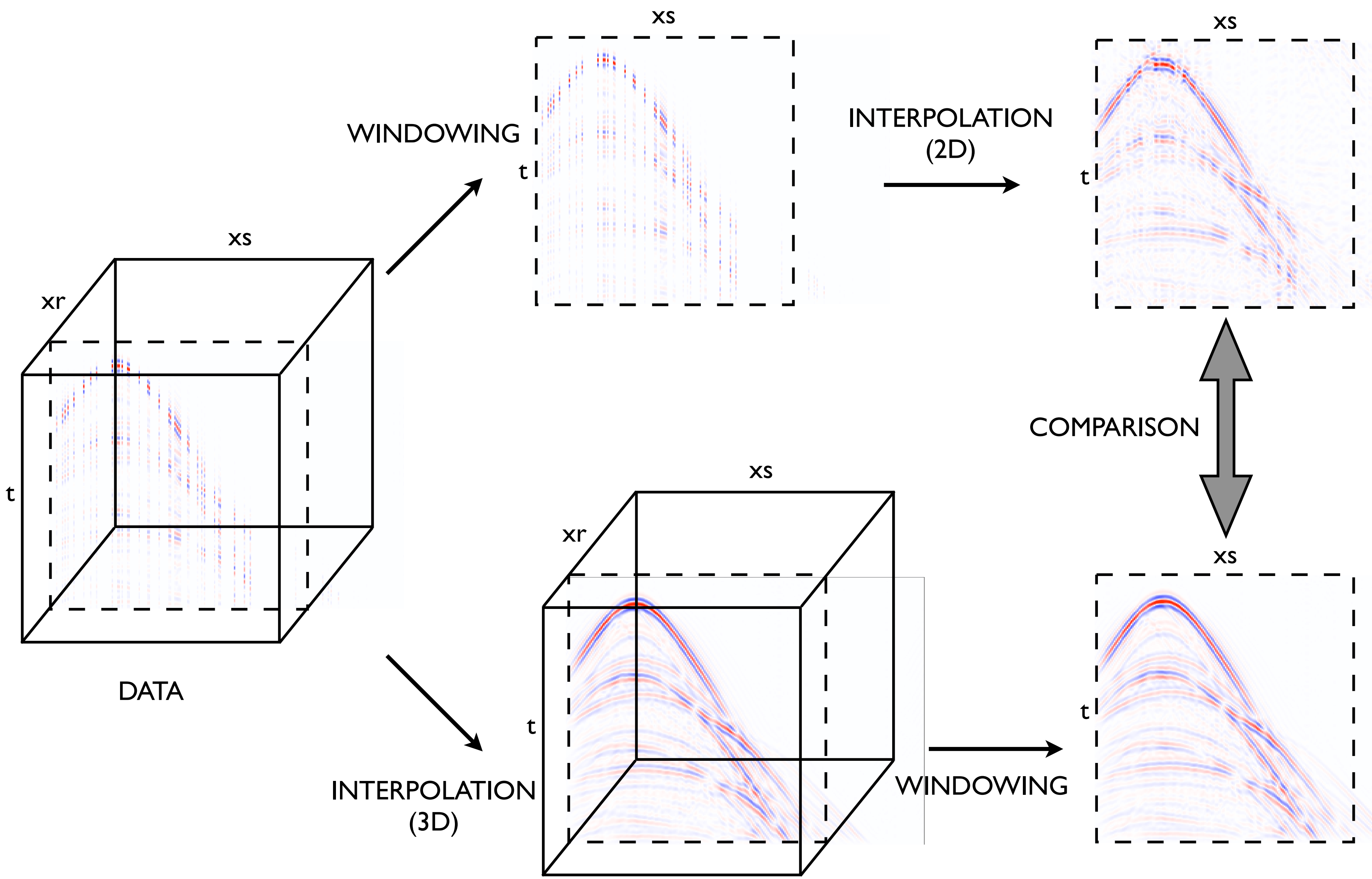
spatial sampling: 12.5 m

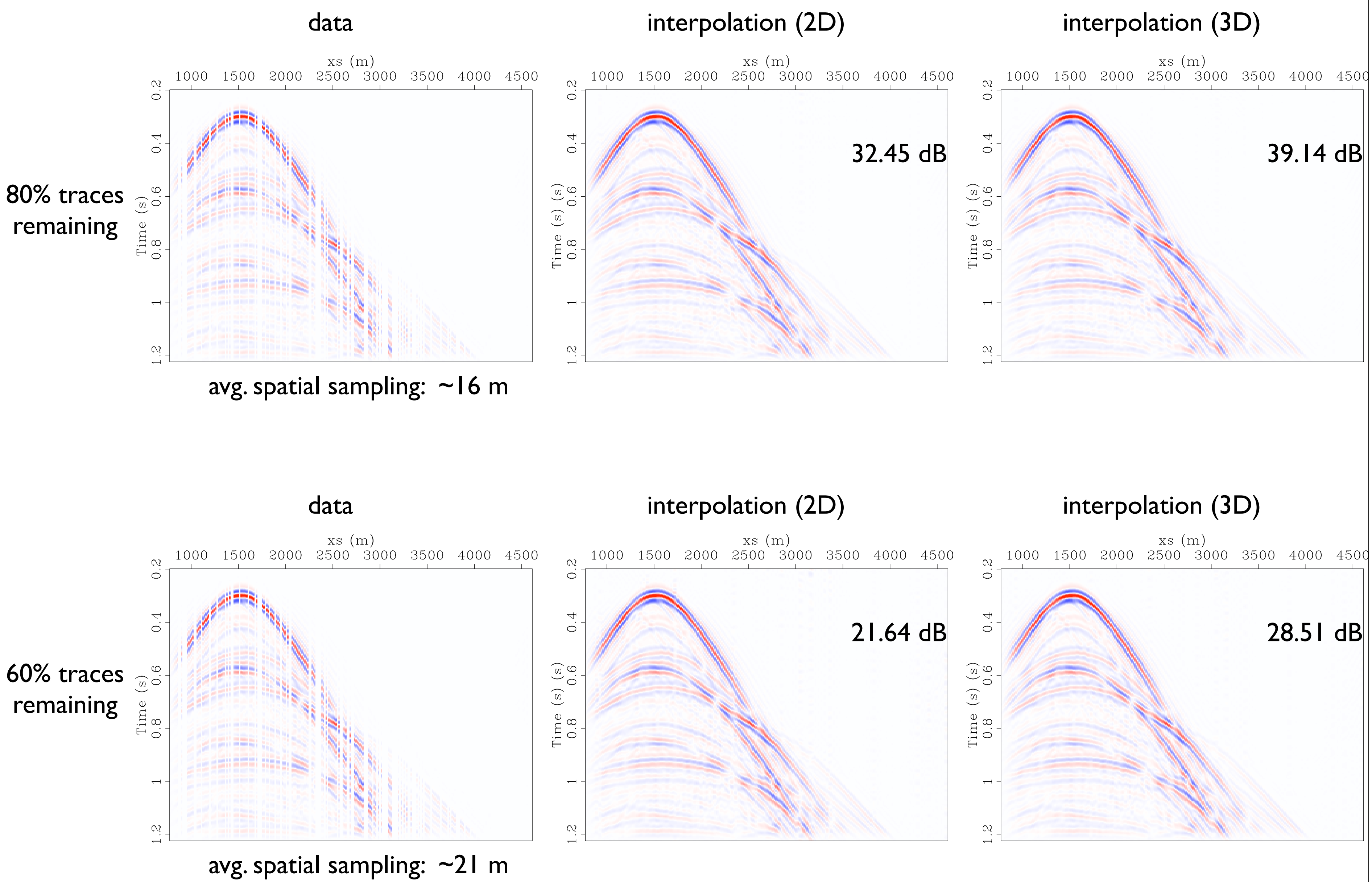


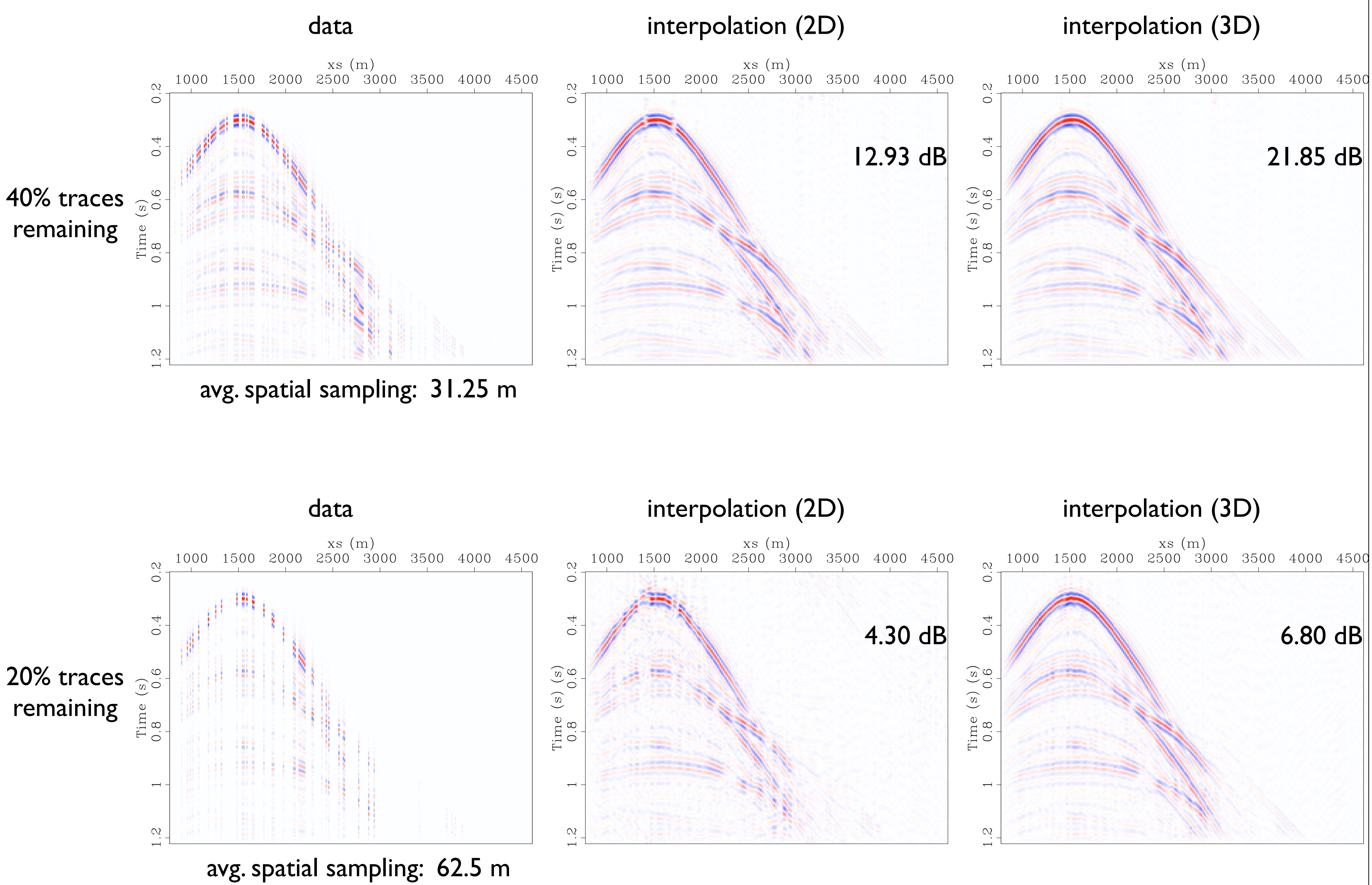


20% traces remaining

avg. spatial sampling: 62.5 m

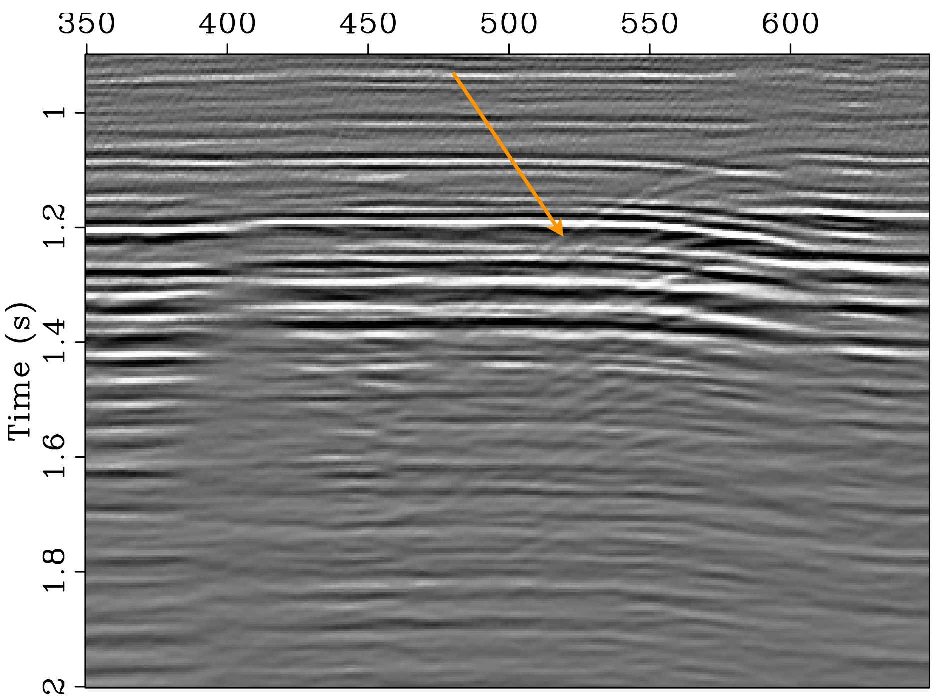

xs
xr
t
DATA
WINDOWING
xs
t
INTERPOLATION
(2D)
xs
t
COMPARISON
INTERPOLATION
(3D)
xs
xr
t
WINDOWING
xs
t


data
interpolation (2D)
interpolation (3D)
80% traces remaining
32.45 dB
39.14 dB
avg. spatial sampling: ~16 m
60% traces remaining
21.64 dB
28.51 dB
avg. spatial sampling: ~21 m
xs (m)
Time (s)
1000 1500 2000 2500 3000 3500 4000 4500
0.2 0.4 0.6 0.8 1 1.2

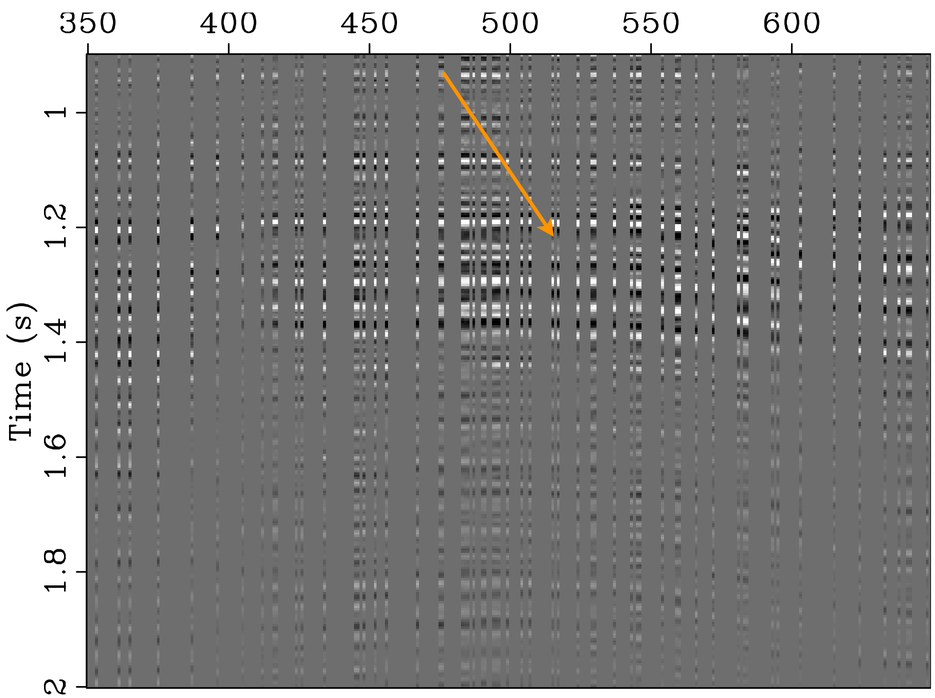


data
interpolation (2D)
interpolation (3D)
40% traces remaining
xs (m)
Time (s)
12.93 dB
21.85 dB
avg. spatial sampling: 31.25 m
20% traces remaining
4.30 dB
6.80 dB
avg. spatial sampling: 62.5 m

From 62.5 m to 12.5 m

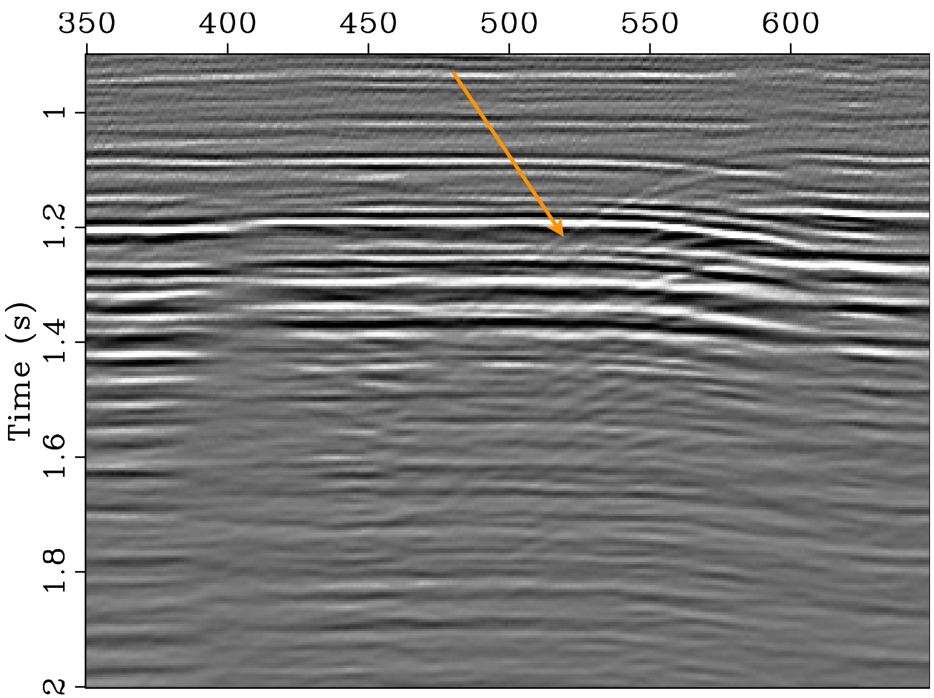


Original data

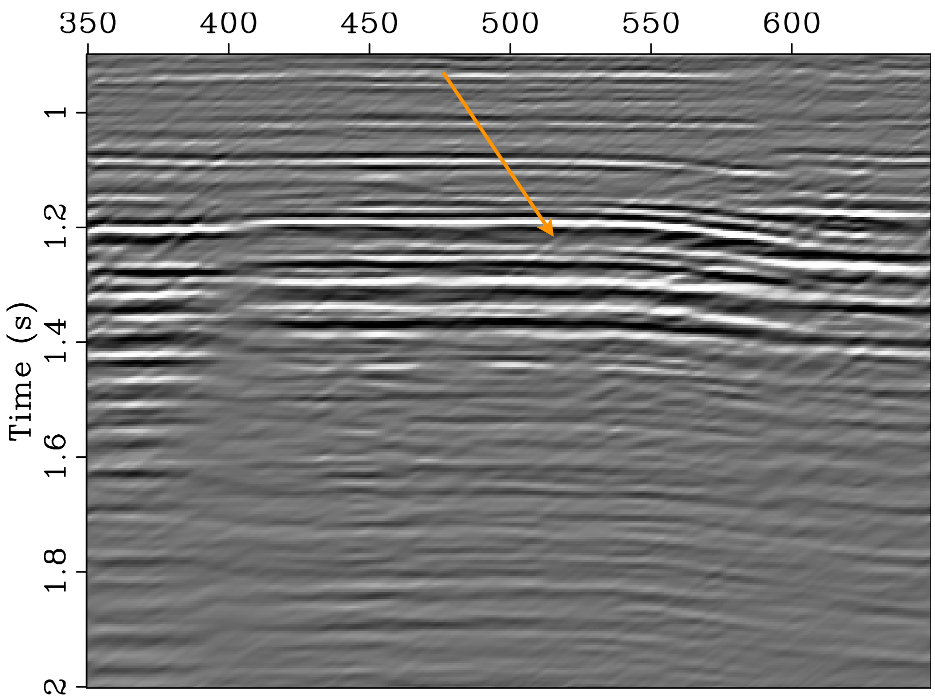


Input data

From 62.5 m to 12.5 m

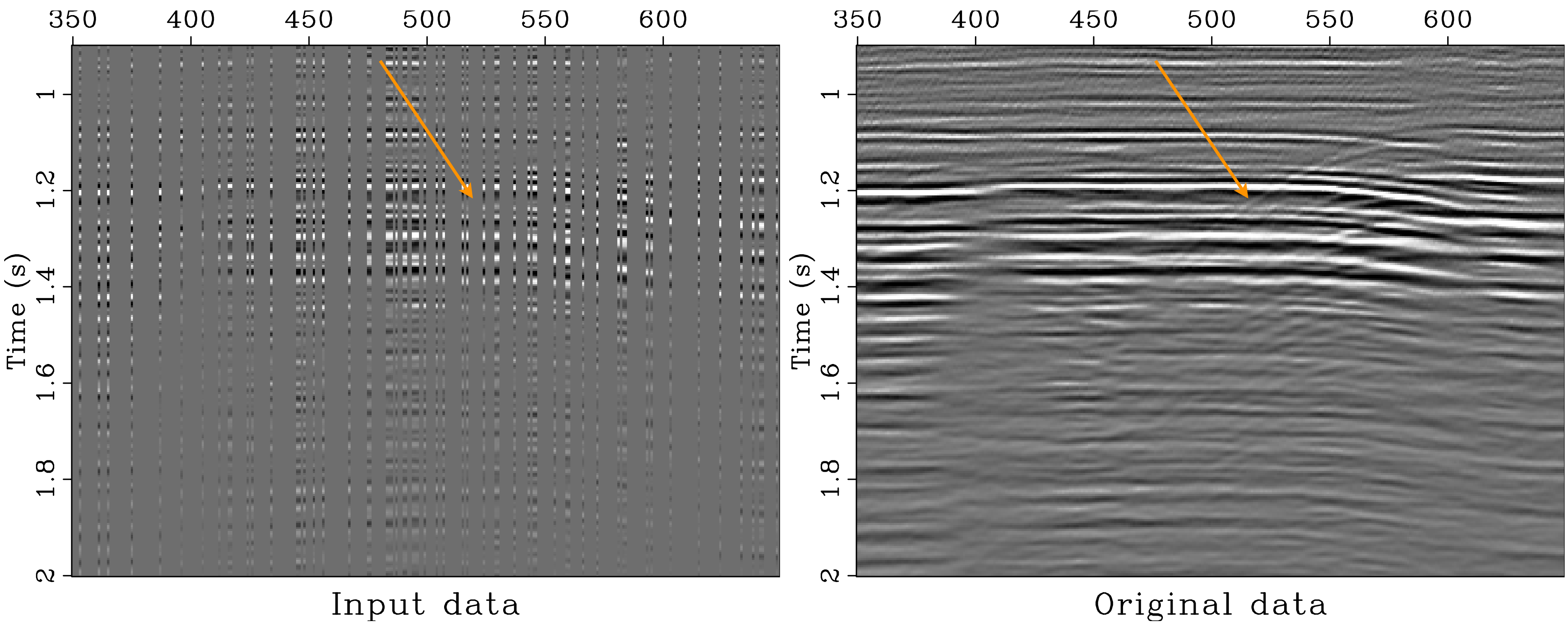


Original data

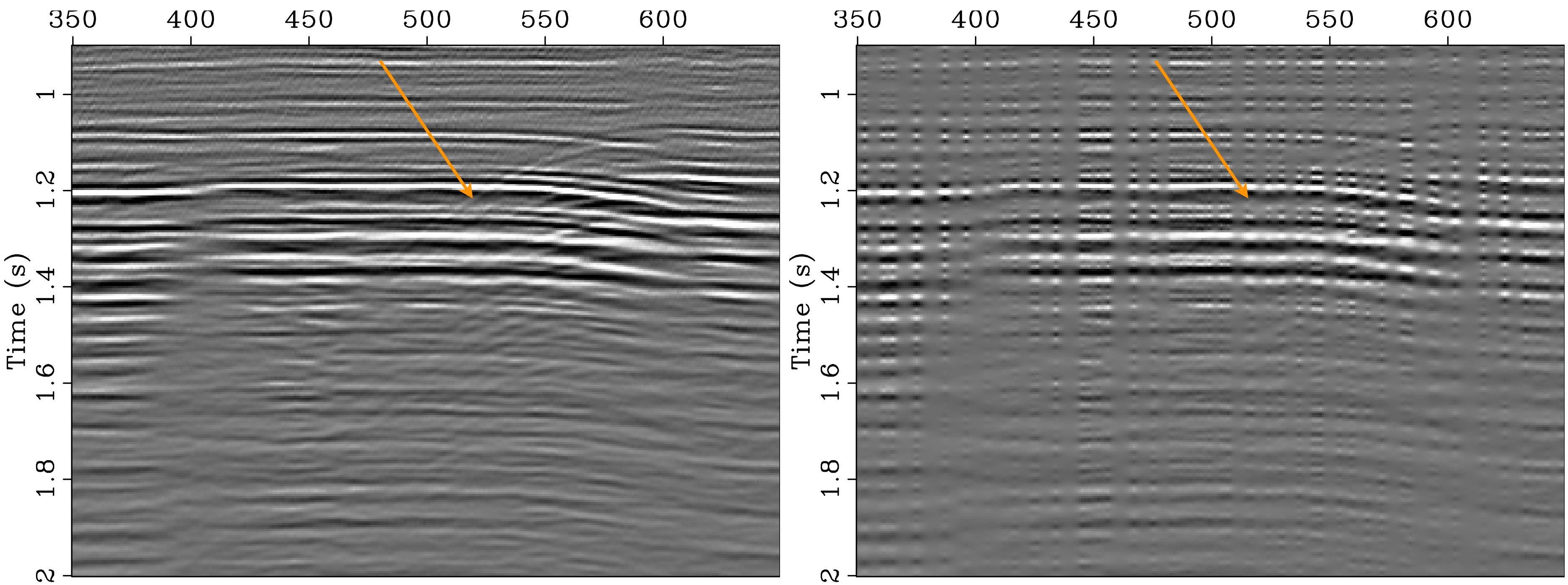


CRSI interpolated result

From 62.5 m to 12.5 m



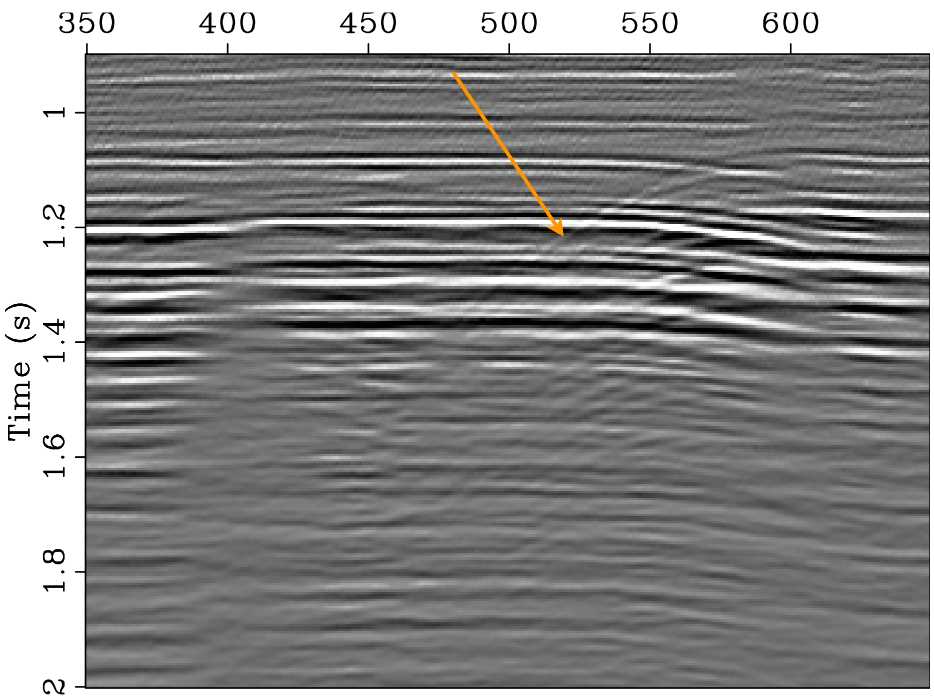
From 62.5 m to 12.5 m



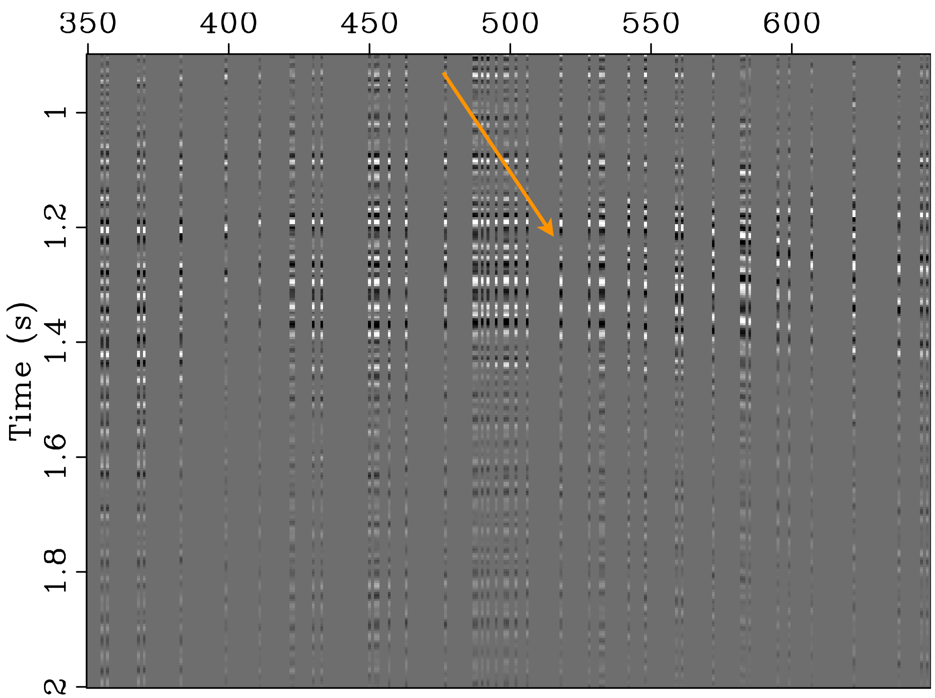
Original data

Laplacian reg. interpolated result

From 84 m to 12.5 m



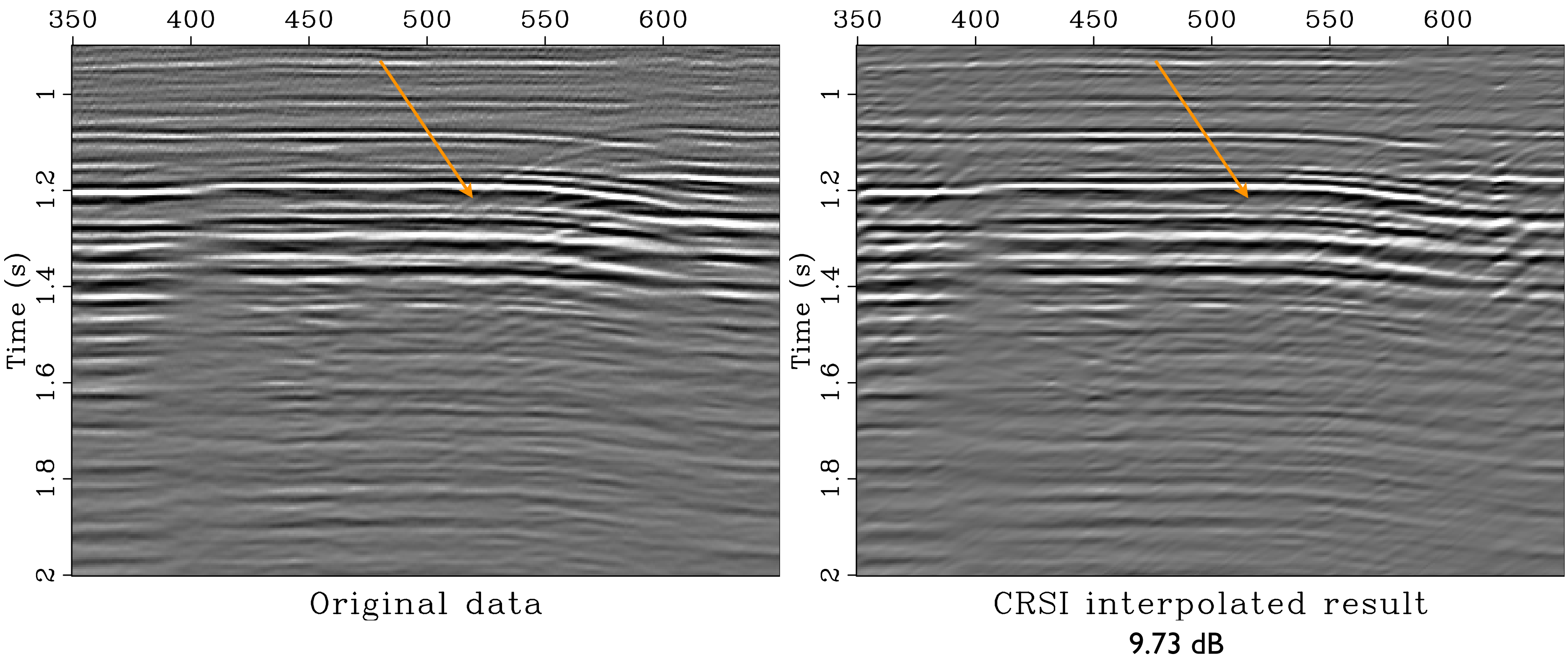
Original data



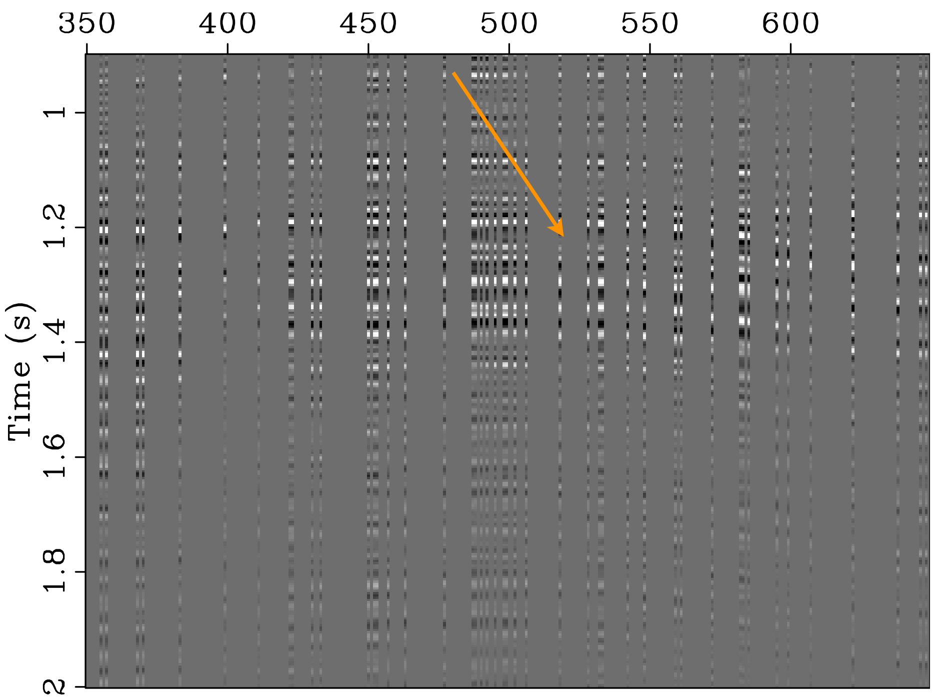
Input data

reproducible figure(s)*

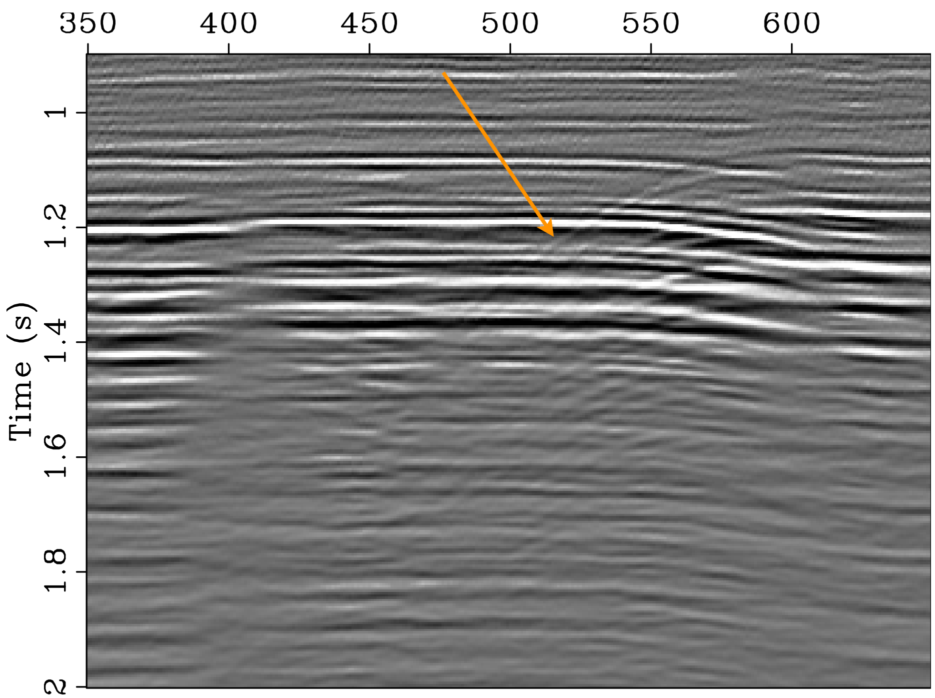
From 84 m to 12.5 m



From 84 m to 12.5 m



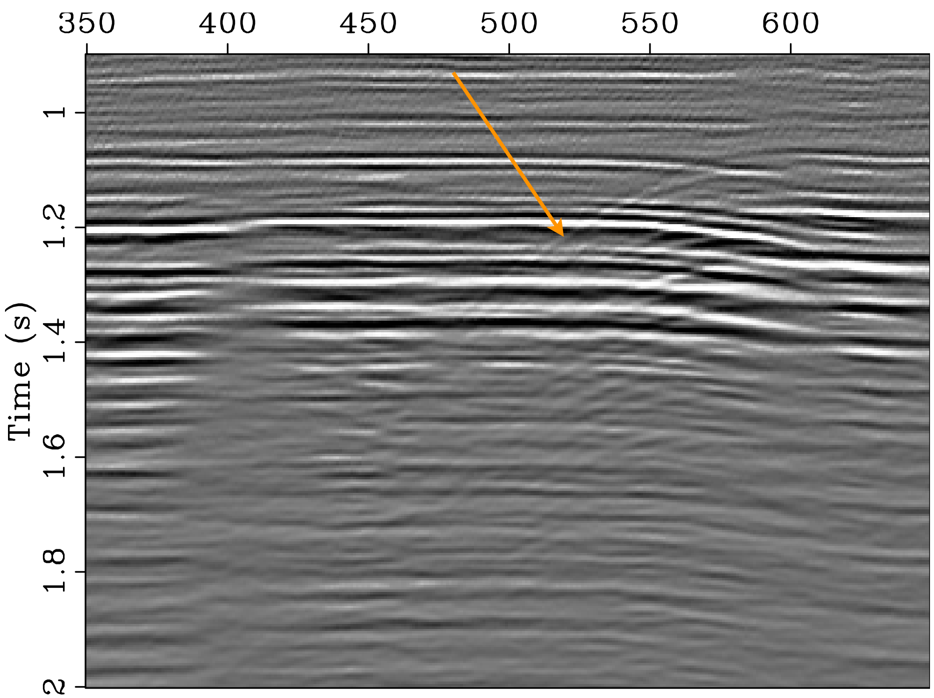
Input data



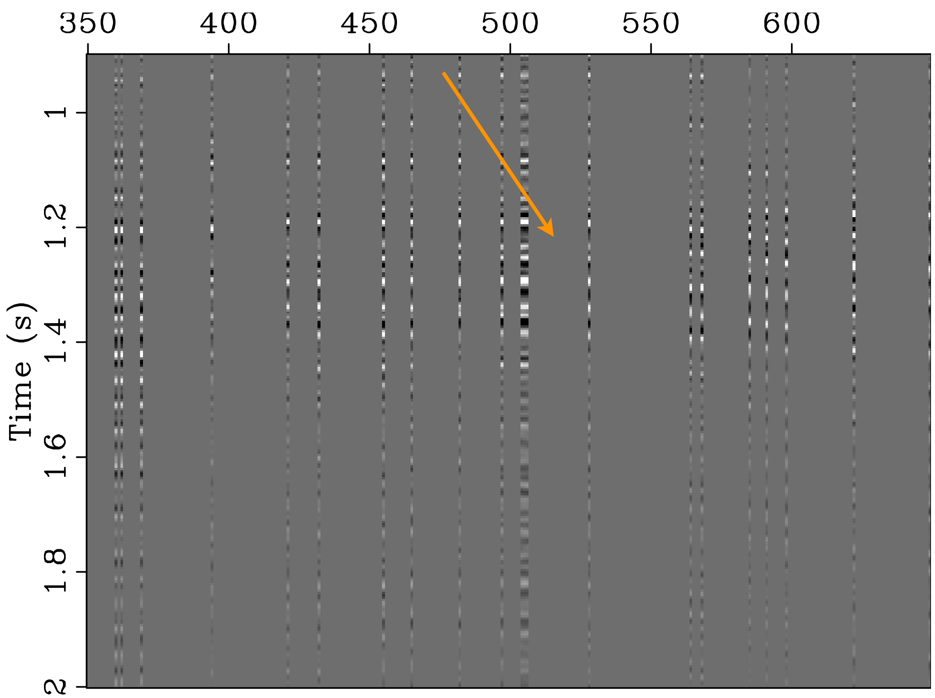
Original data

reproducible figure(s)*

From 180 m to 12.5 m



Original data



Input data2

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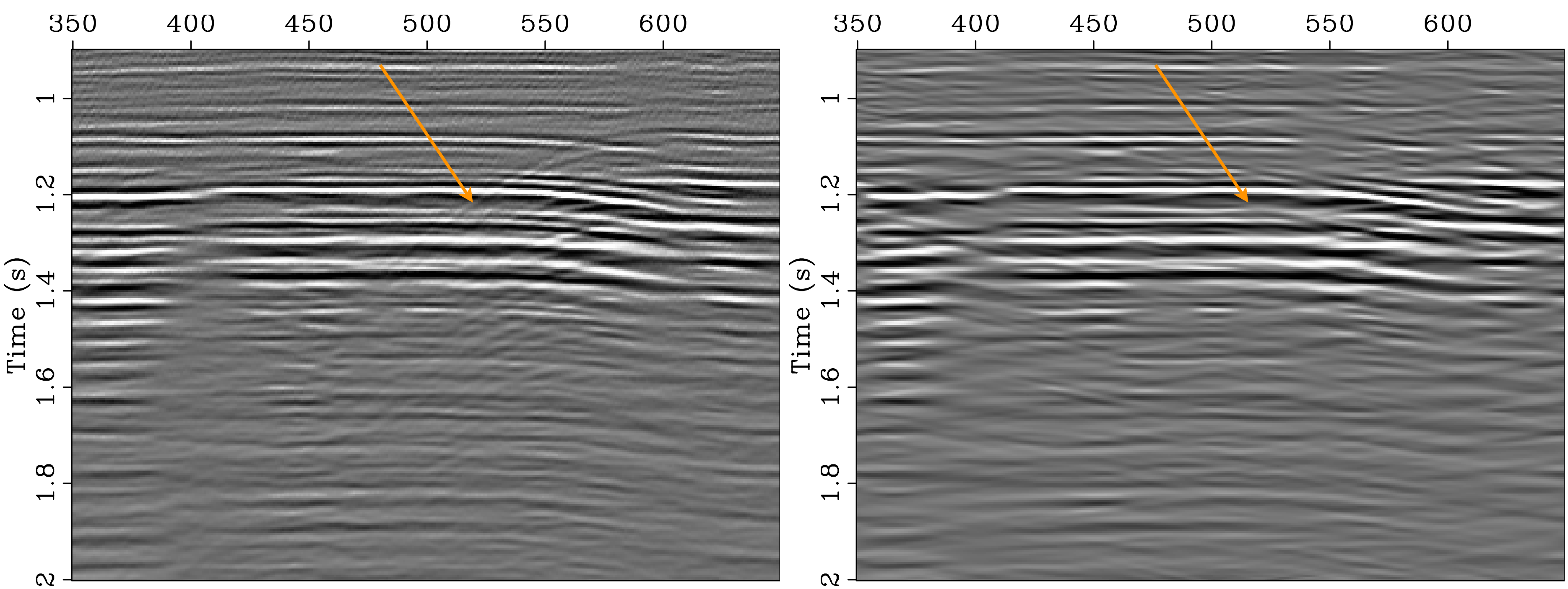
From 180 m to 12.5 m

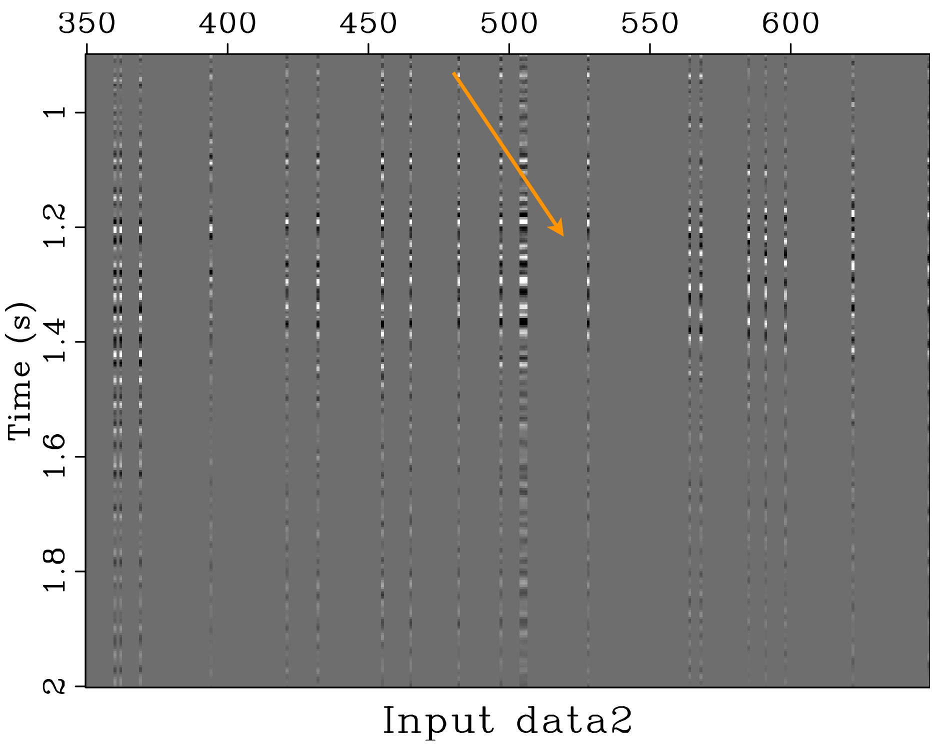


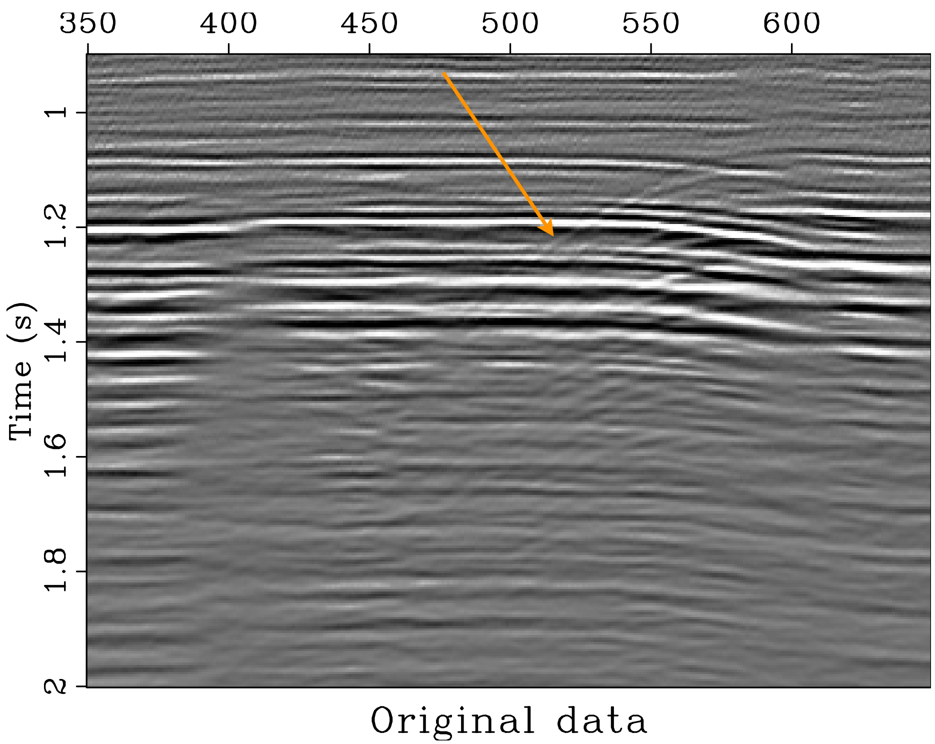
Original data

CRSI2 interpolated result

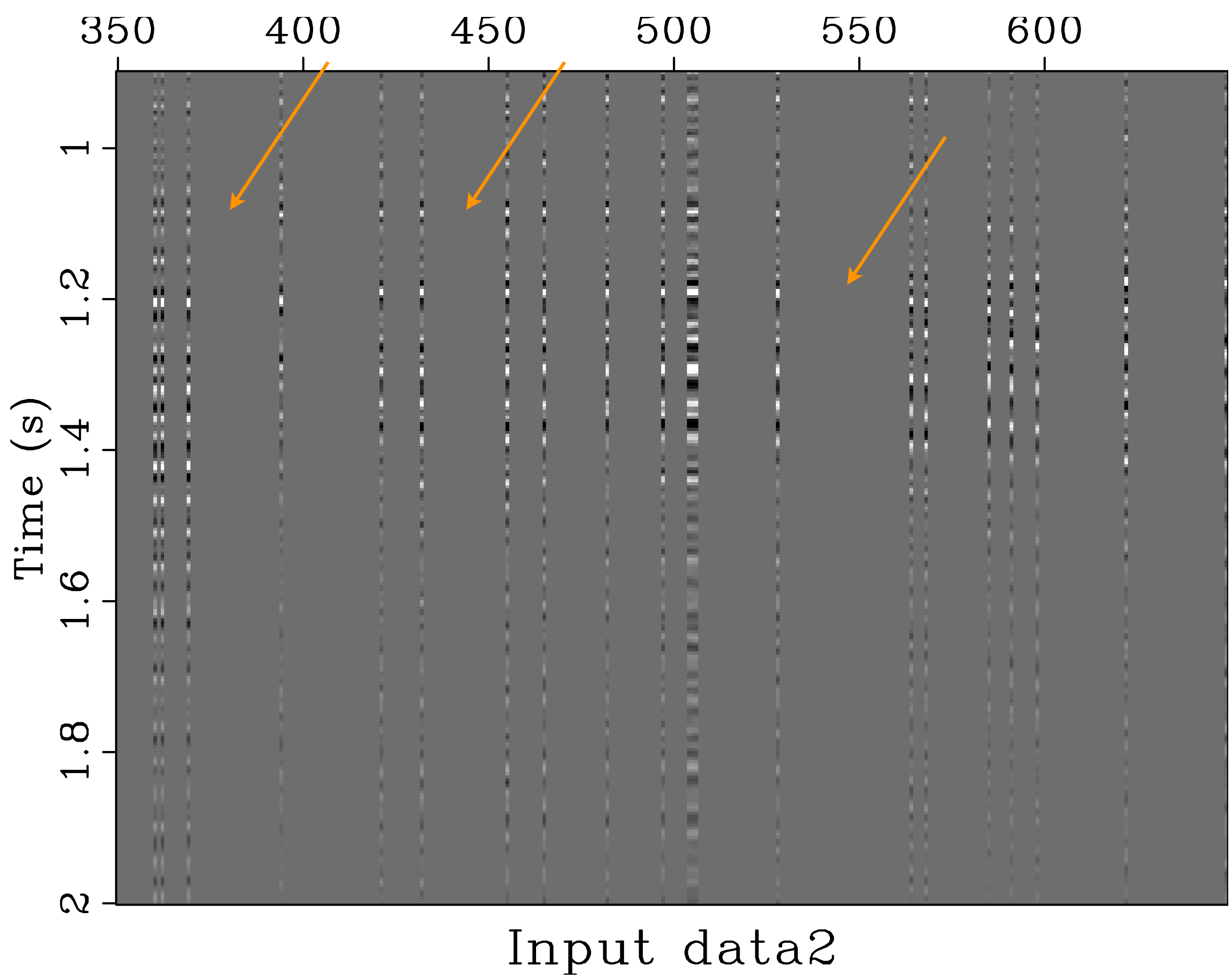
5.64 dB

From 180 m to 12.5 m

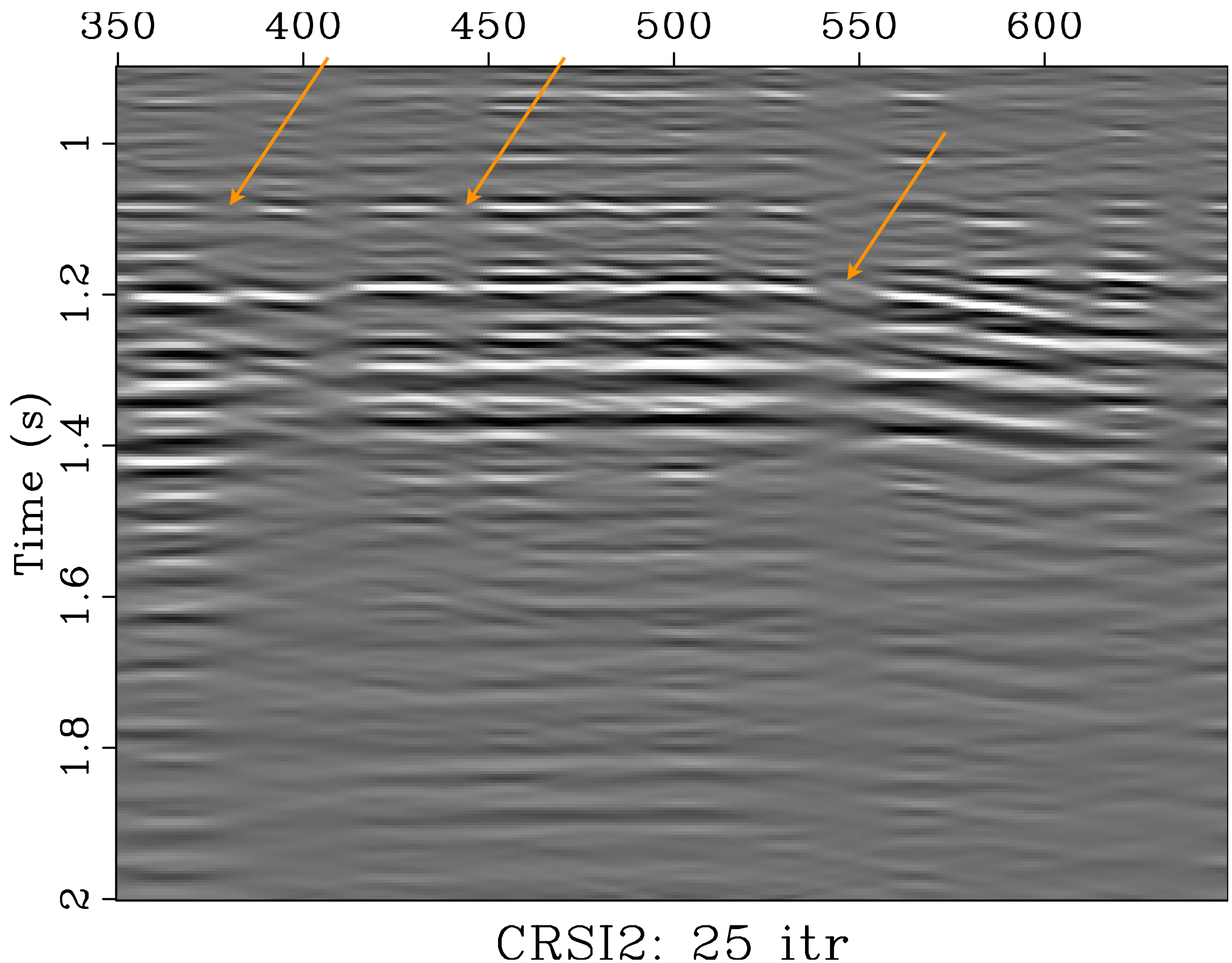




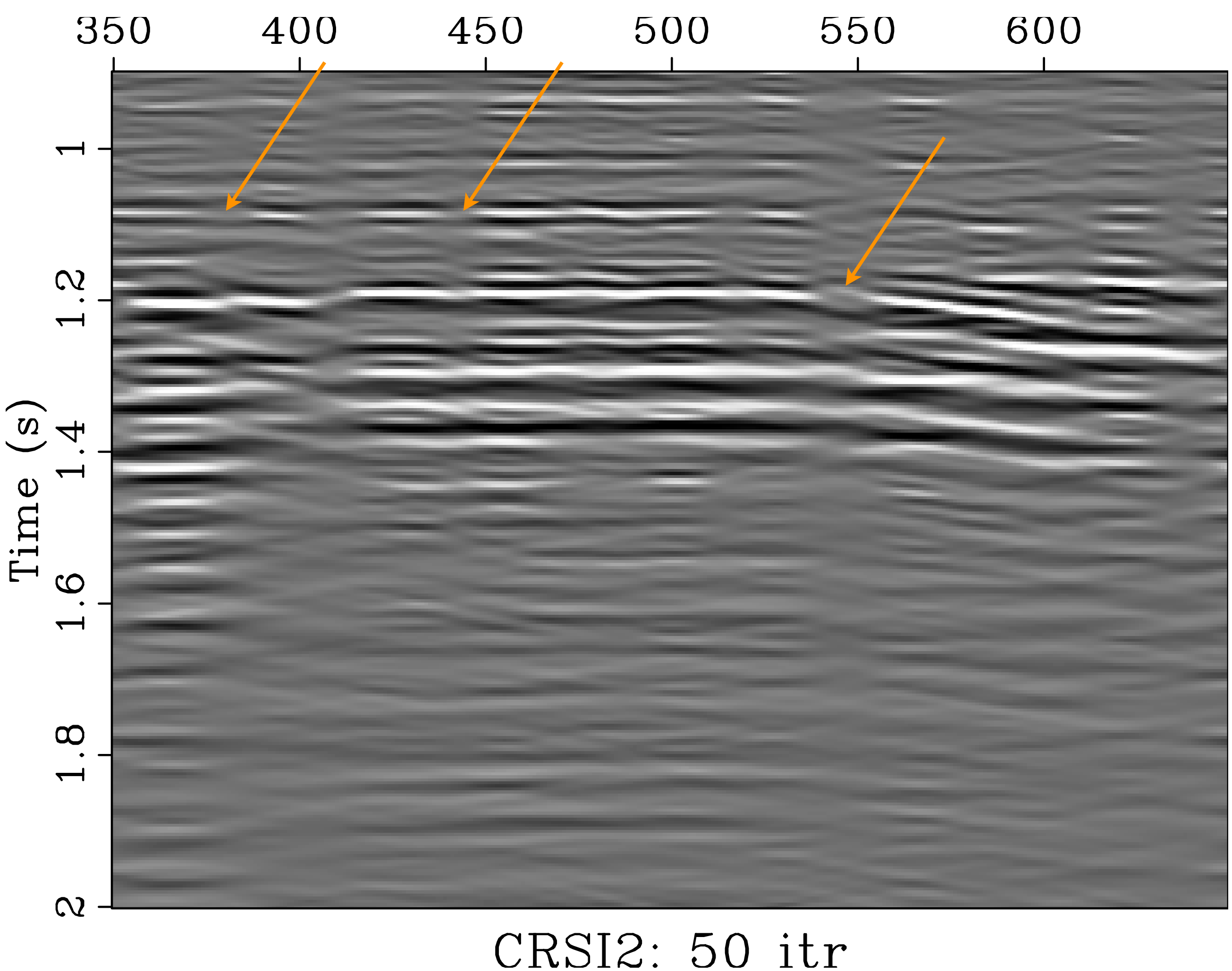
Amplitude recovery with nb. of iterations



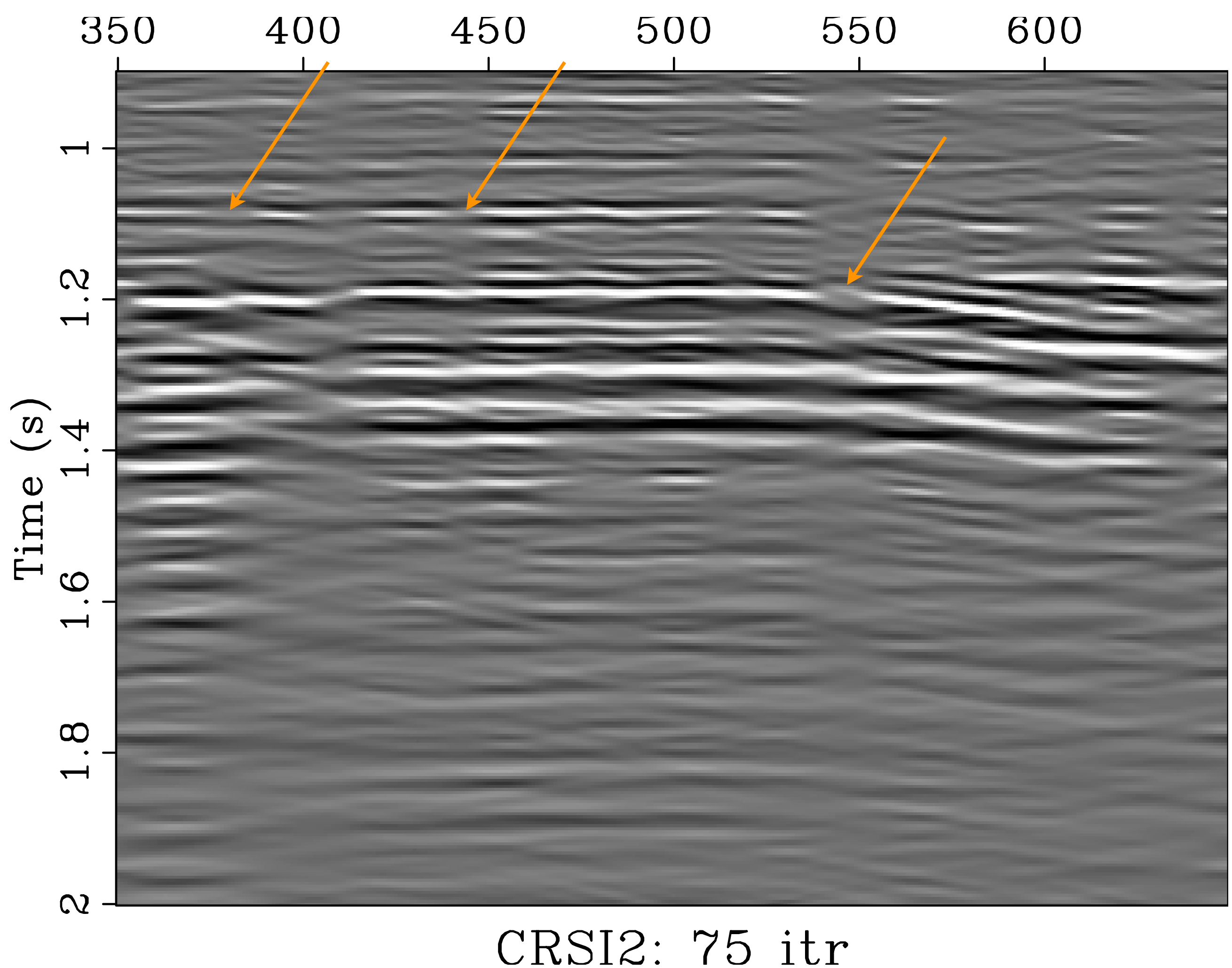
Amplitude recovery with 25 iterations



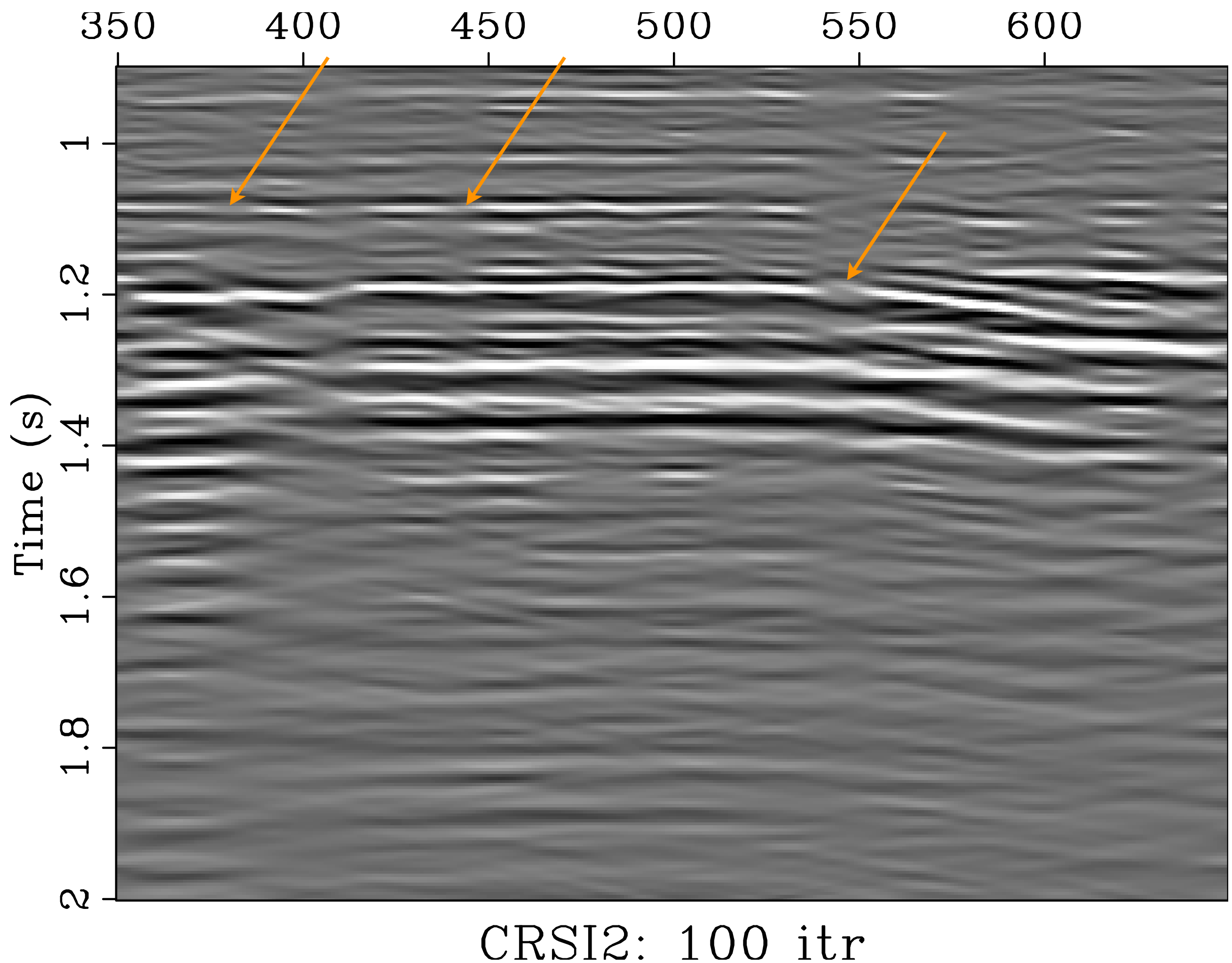
Amplitude recovery with 50 iterations



Amplitude recovery with 75 iterations

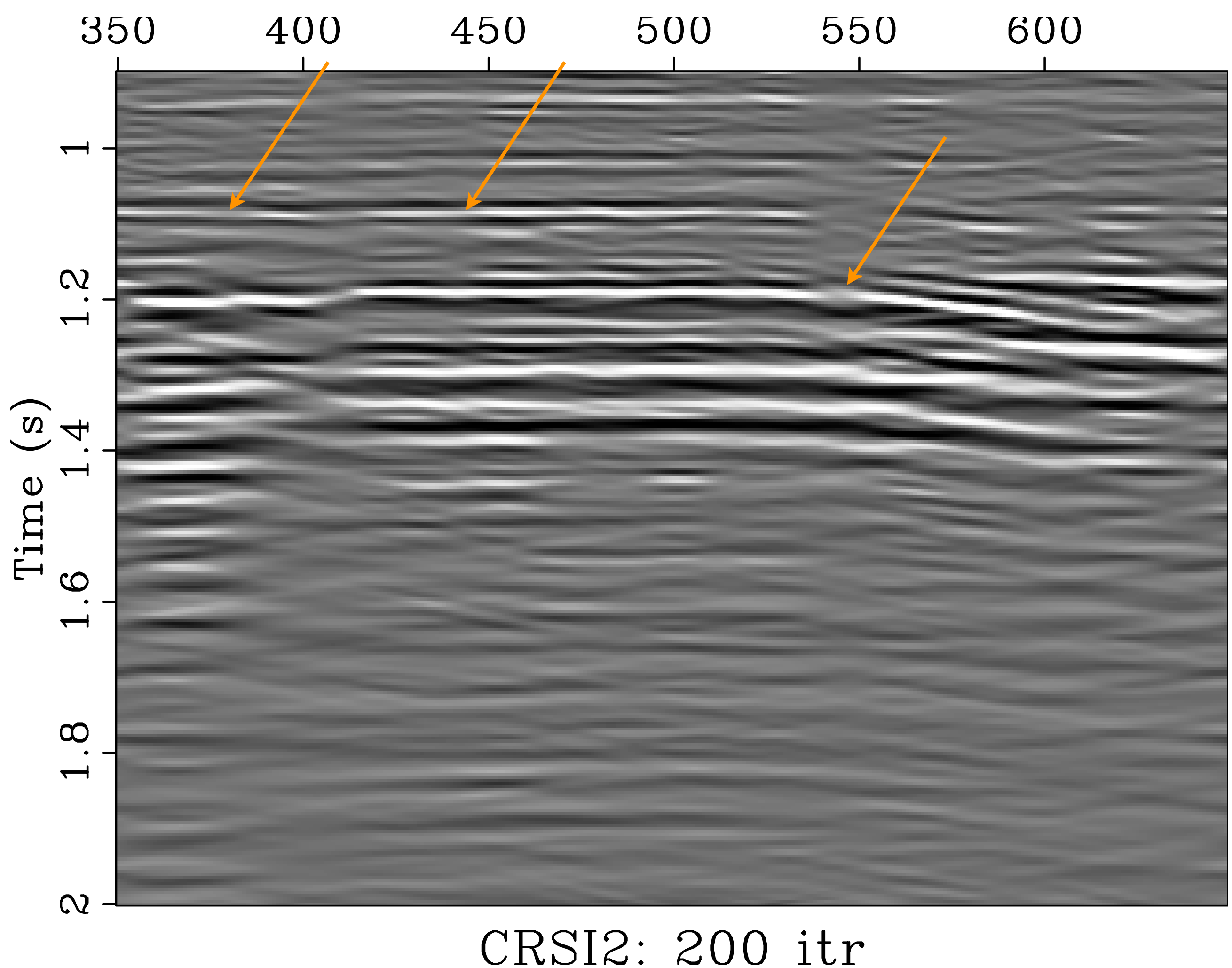


Amplitude recovery with 100 iterations

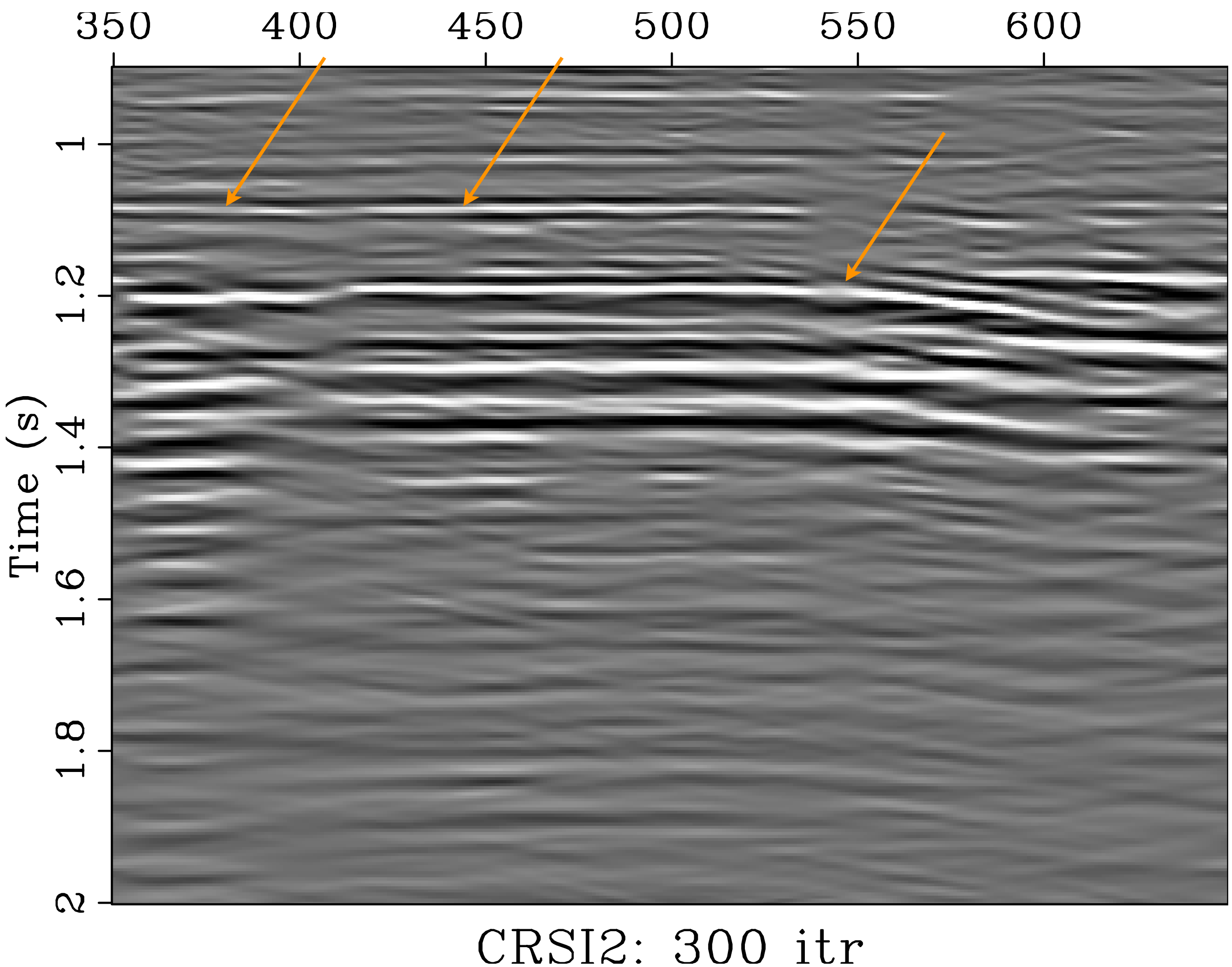


reproducible figure(s)*

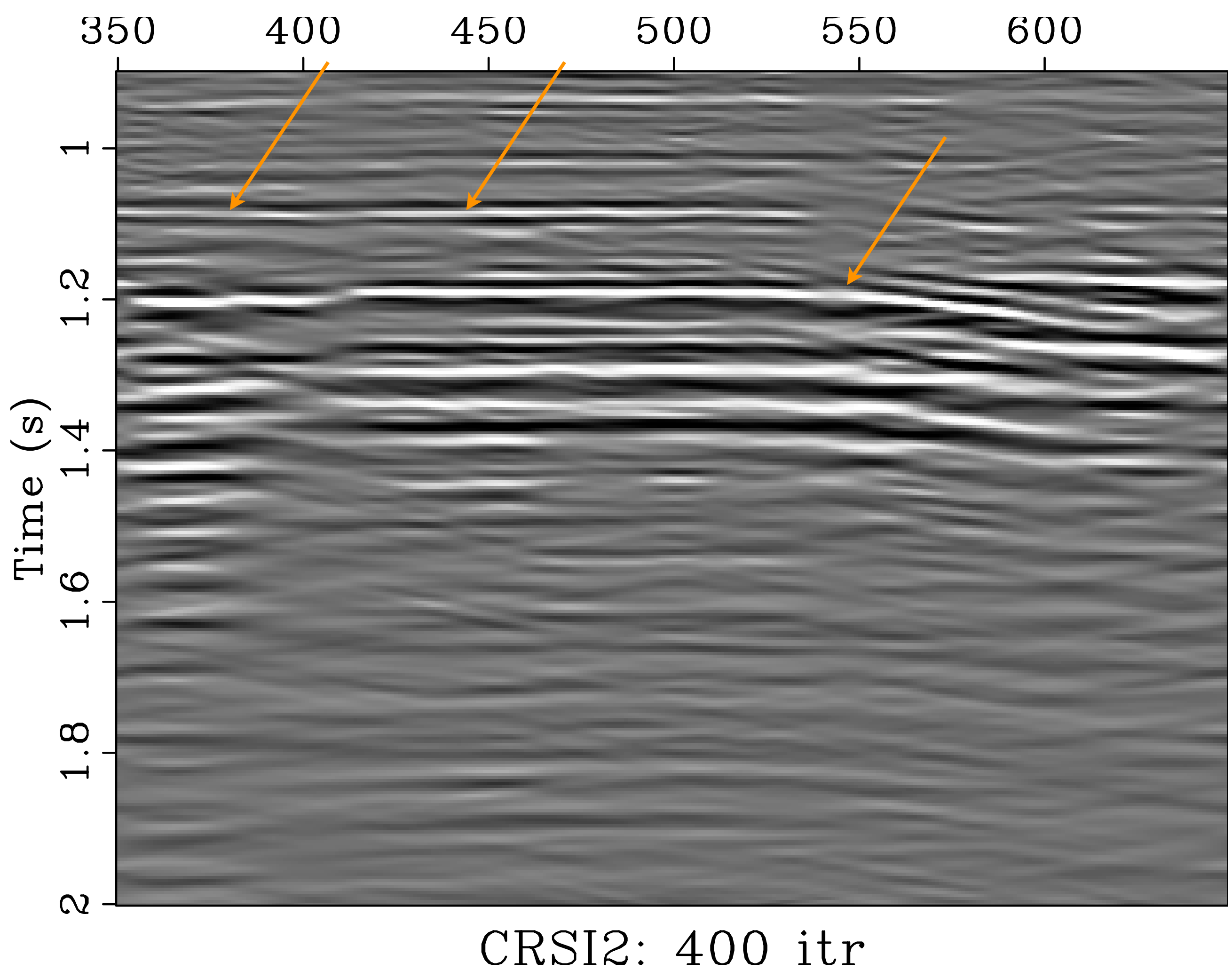
Amplitude recovery with 200 iterations



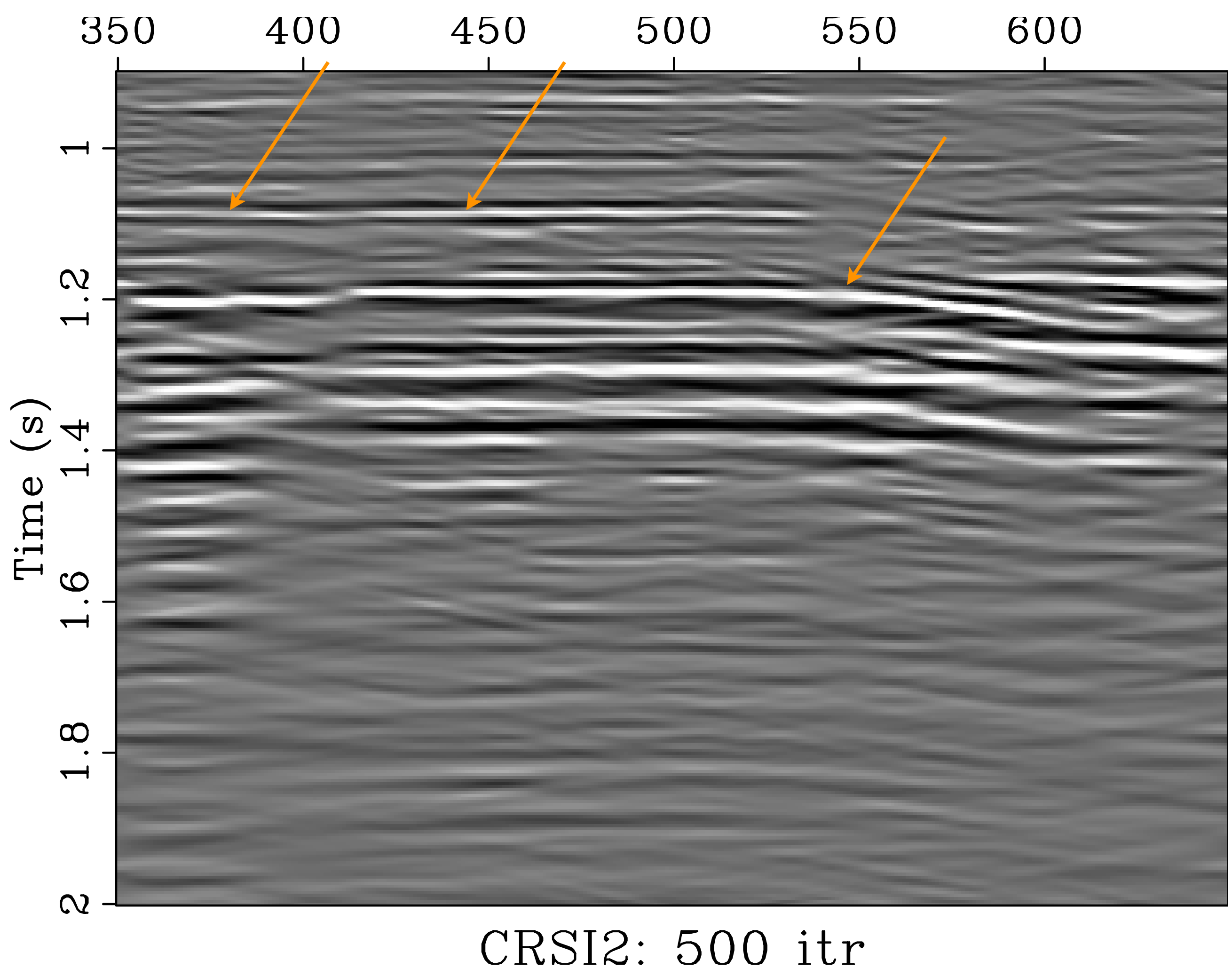
Amplitude recovery with 300 iterations



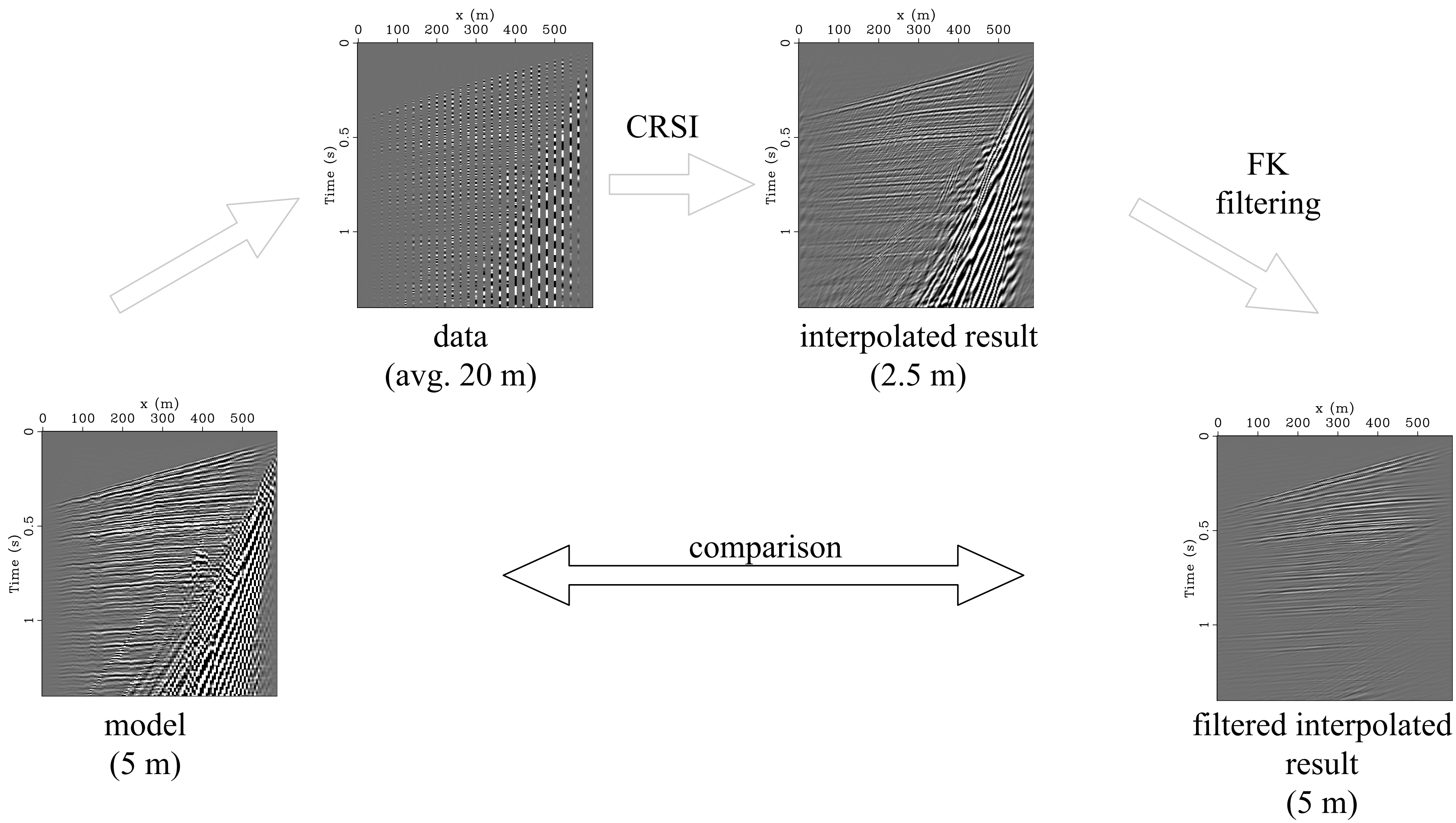
Amplitude recovery with 400 iterations



Amplitude recovery with 500 iterations

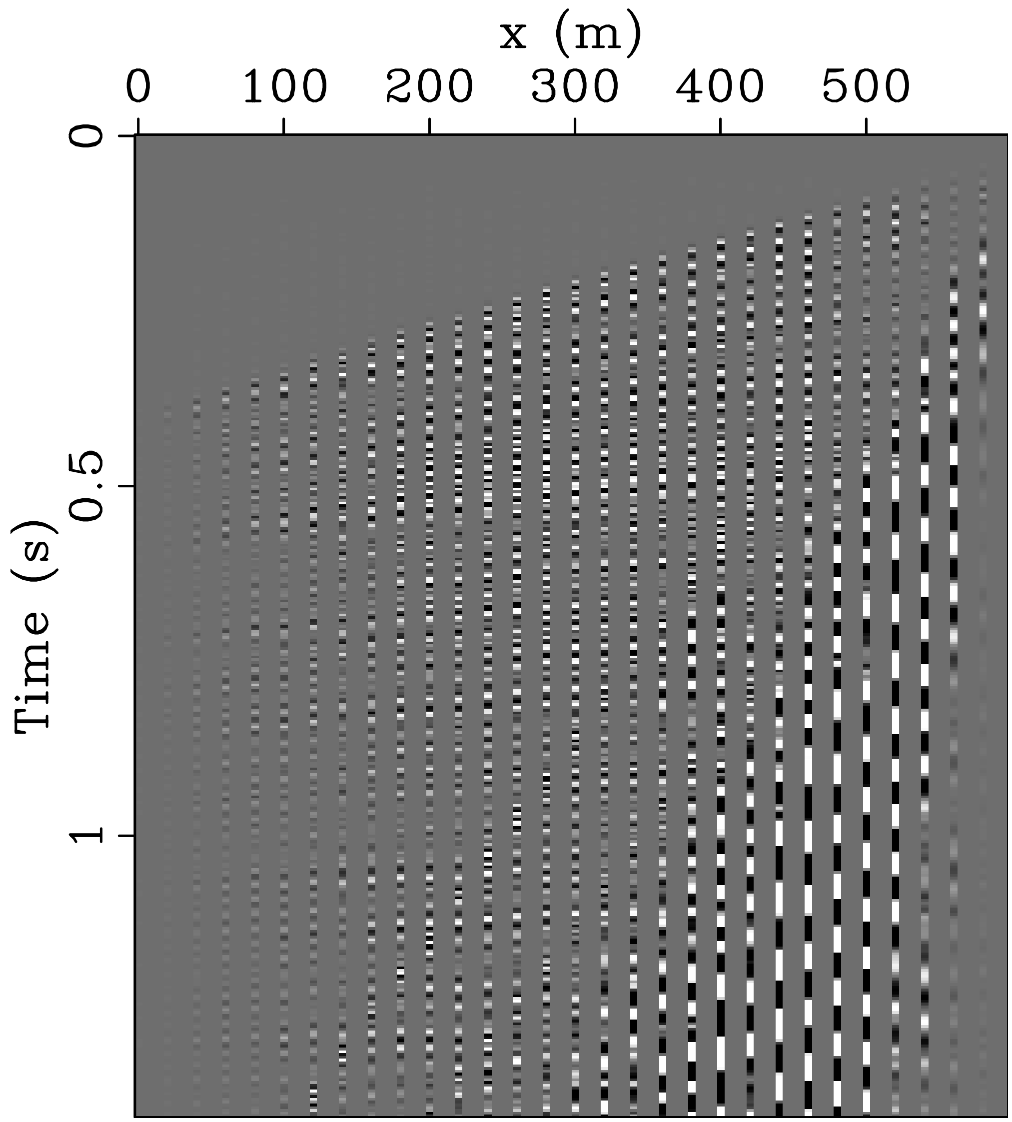


Experiment 1



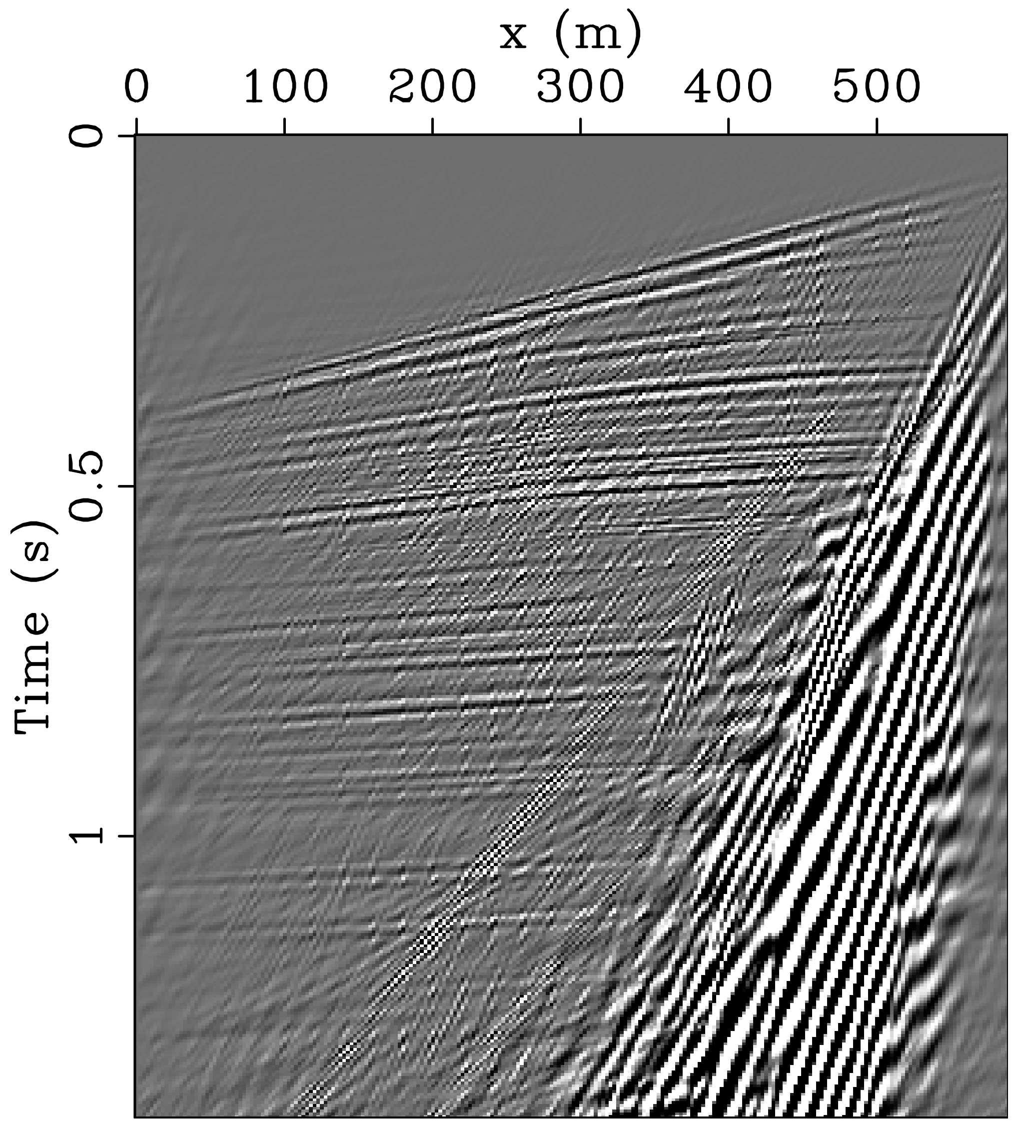
reproducible figure(s)*

Spatial sampling: avg. 20 m



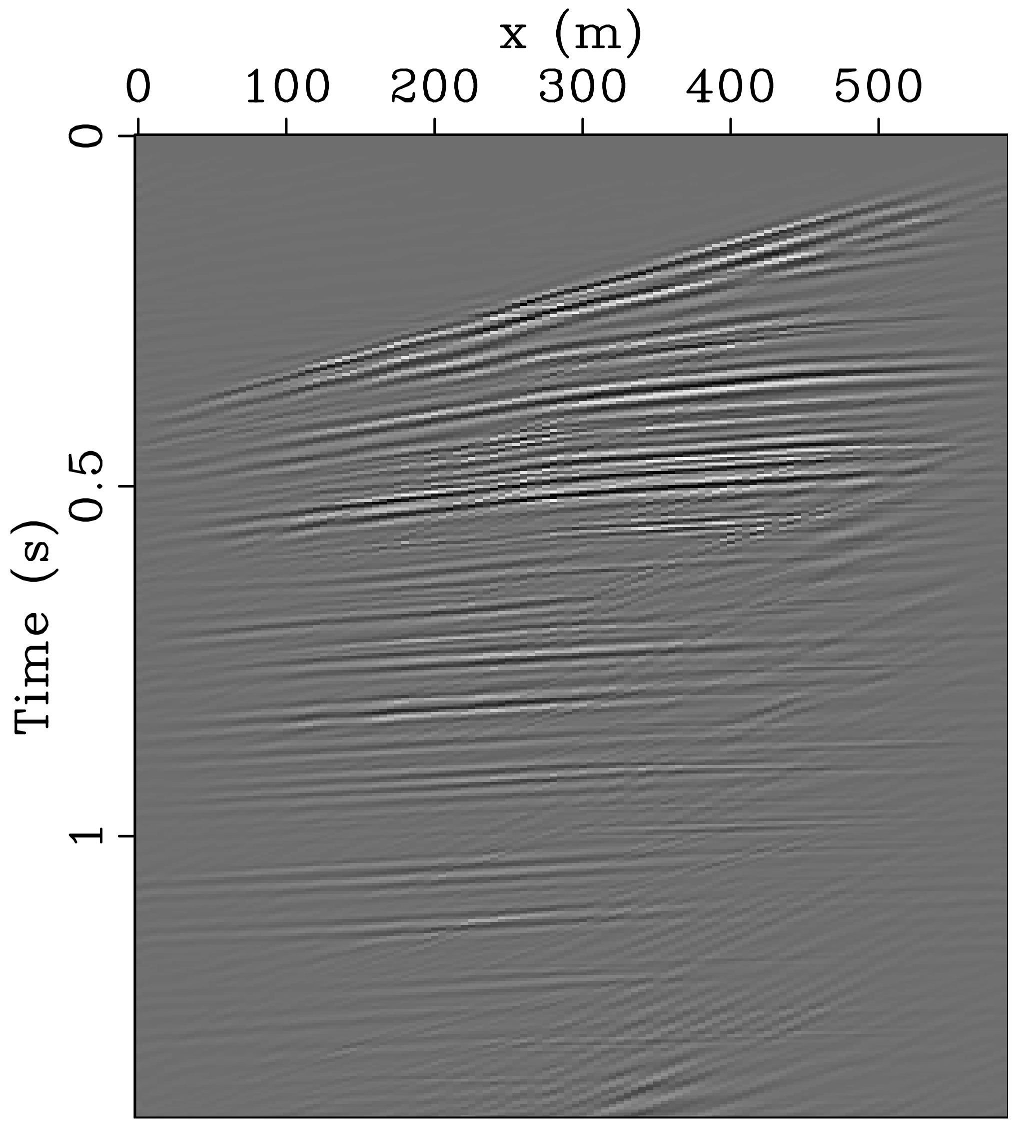
reproducible figure(s)*

From avg. 20 m to 2.5 m

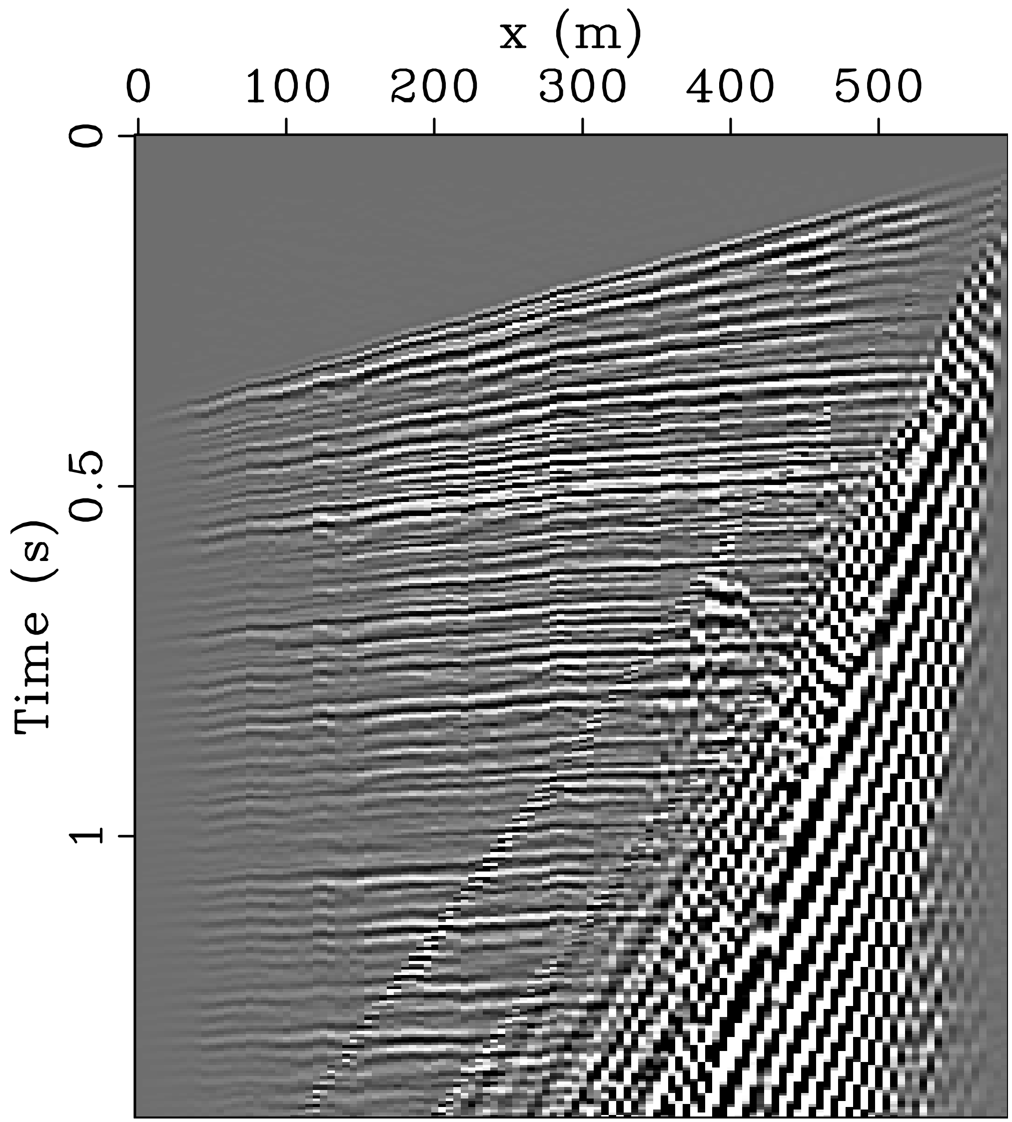


reproducible figure(s)*

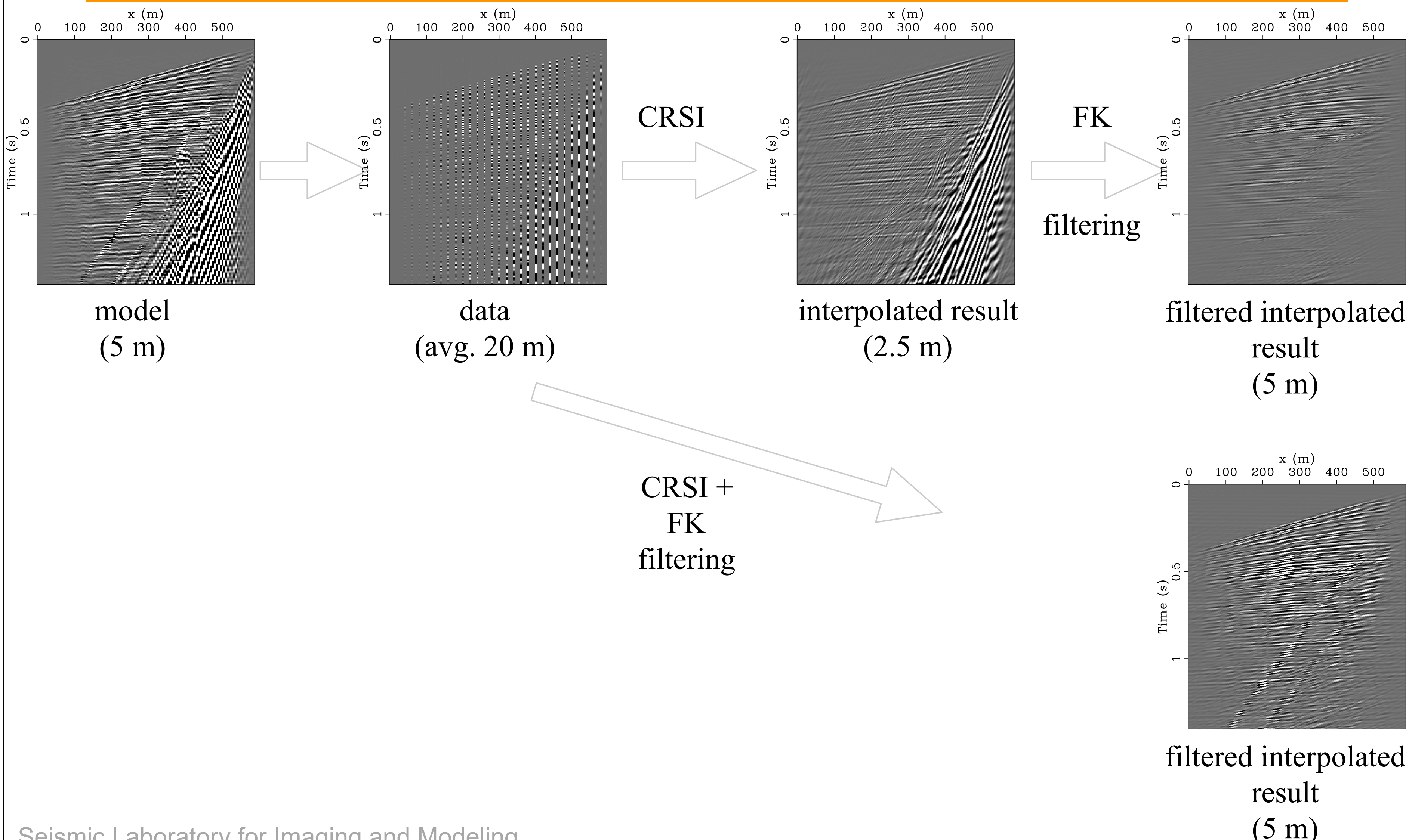
CRSI followed by FK filtering



Model

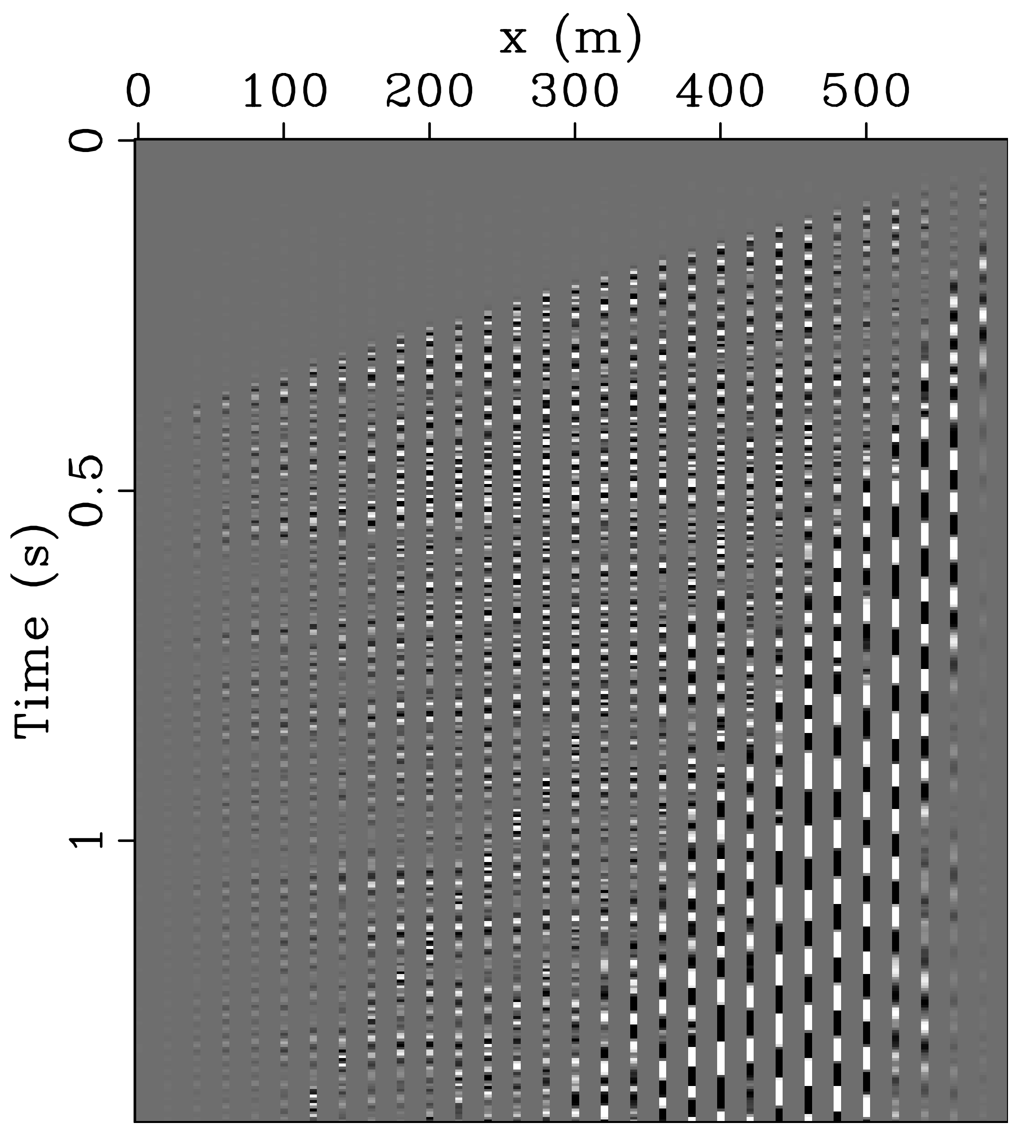


Experiment 2



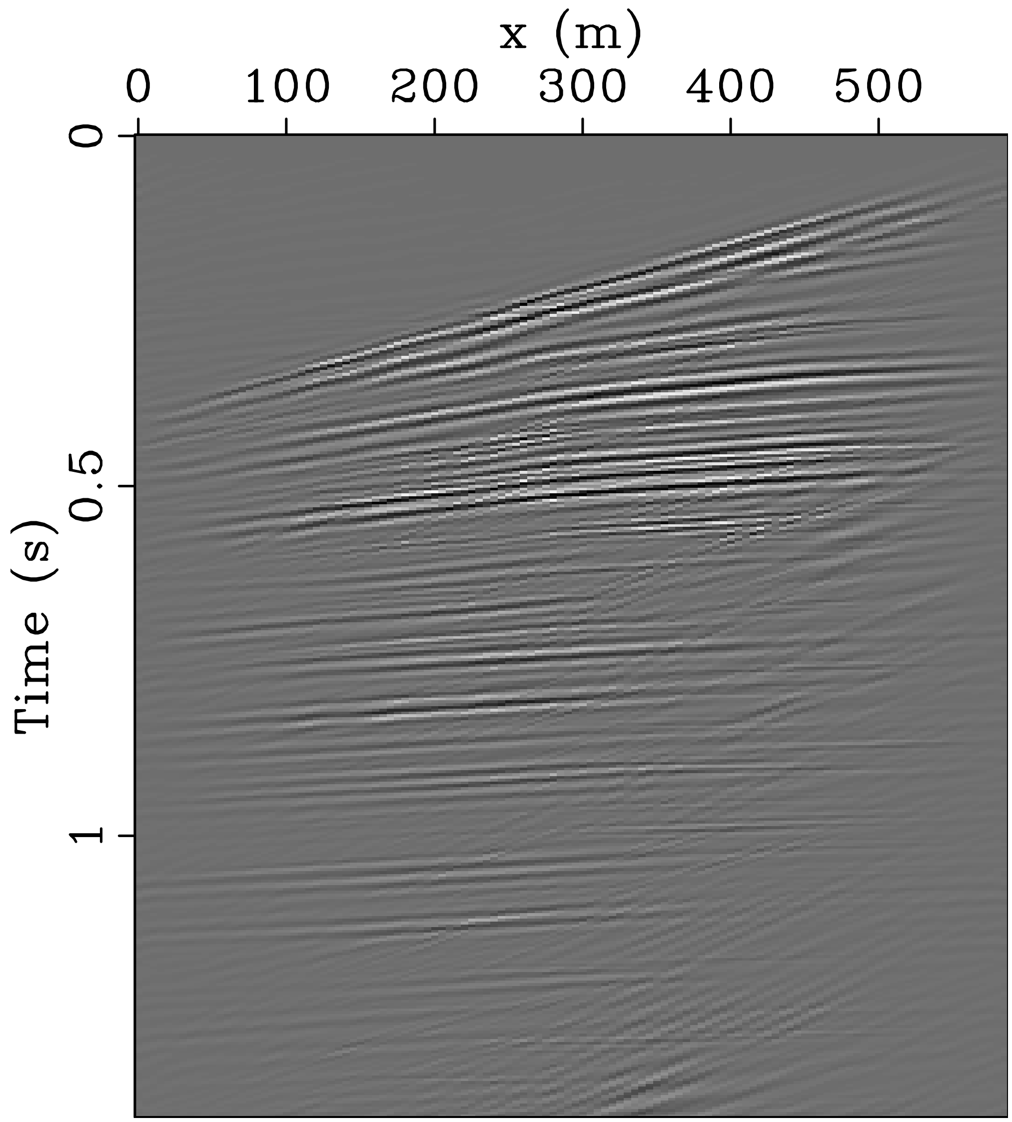
reproducible figure(s)*

Spatial sampling: avg. 20 m



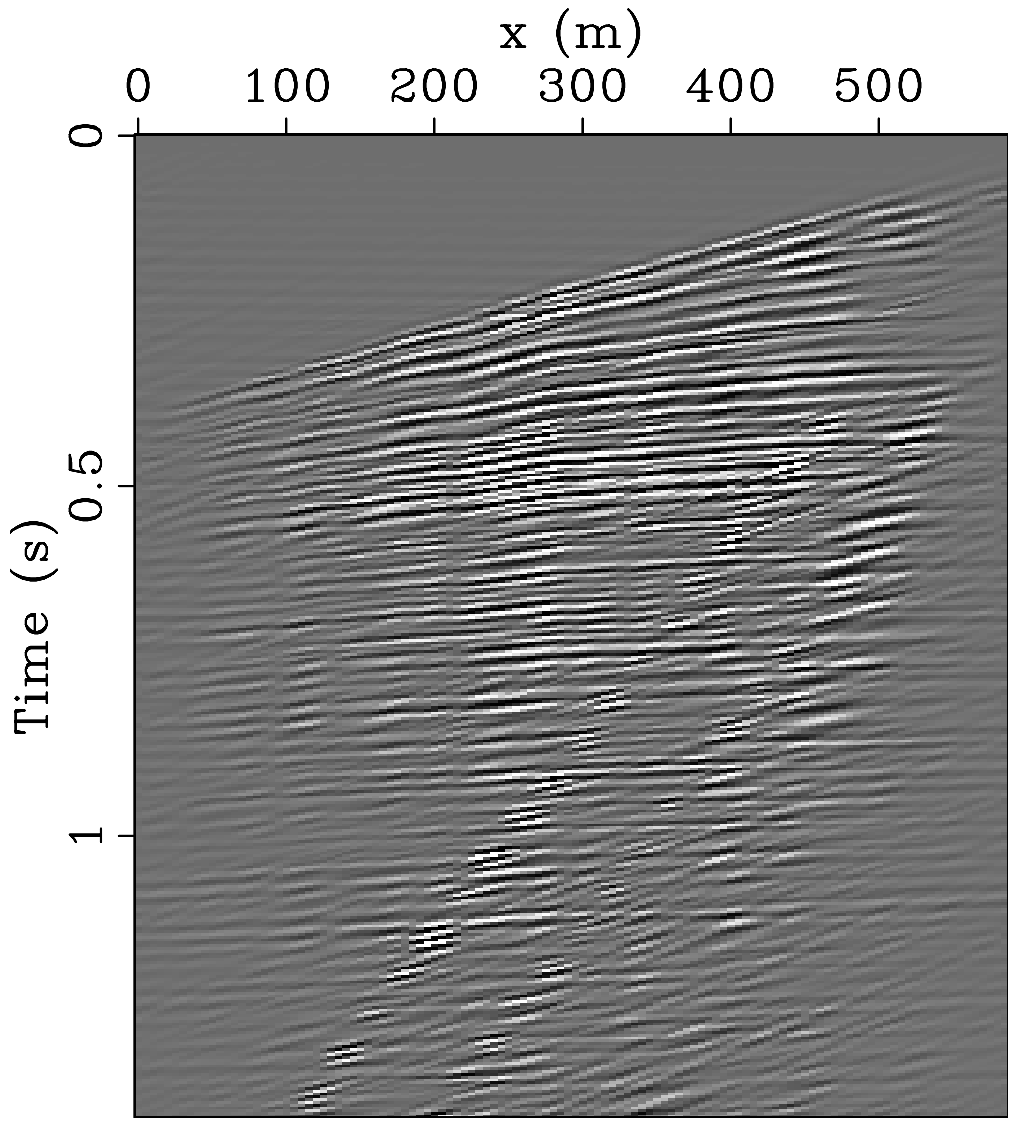
reproducible figure(s)*

CRSI followed by FK filtering

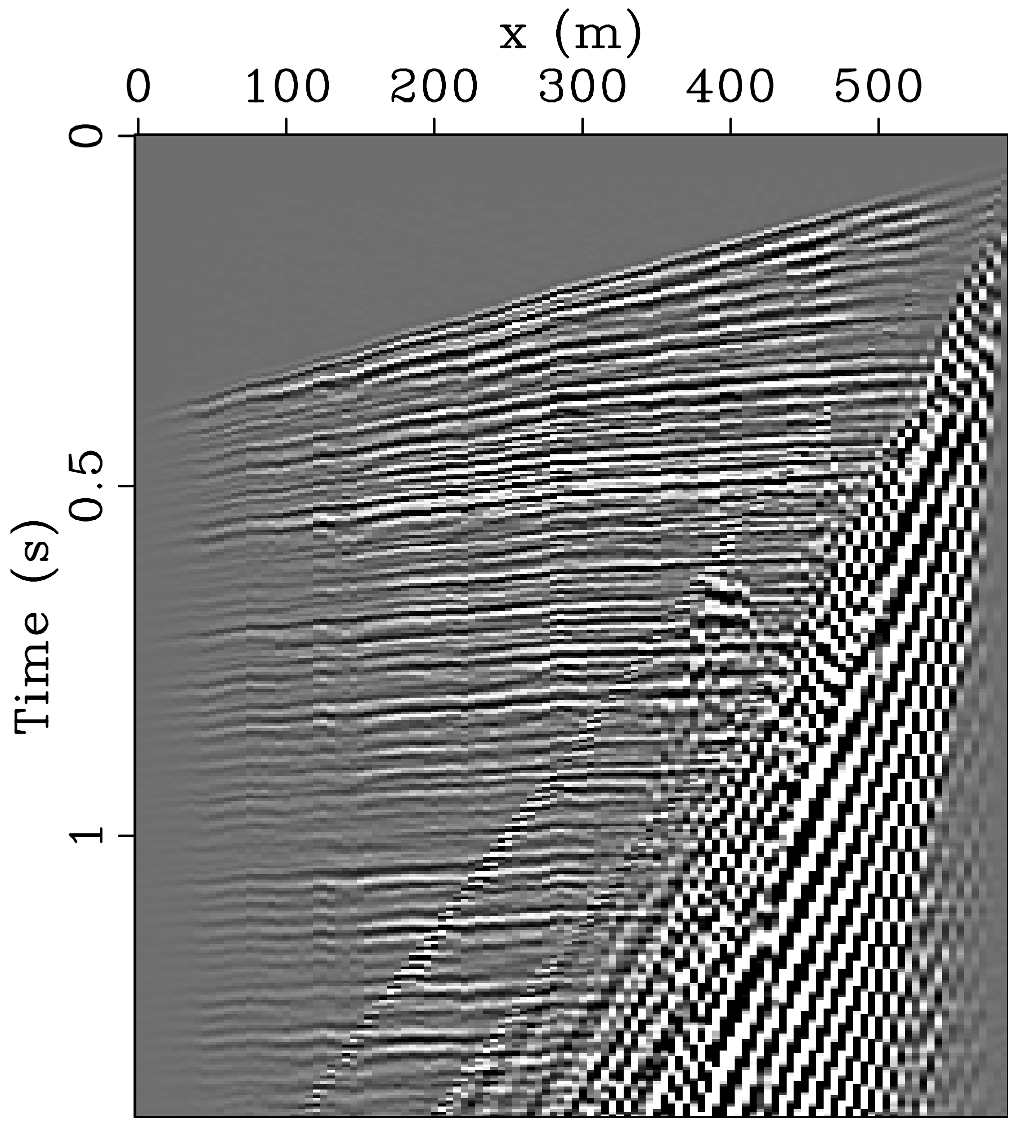


reproducible figure(s)*

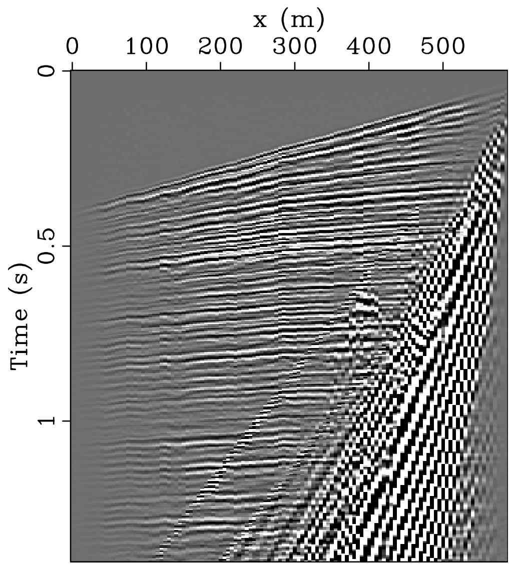
CRSI combined with FK filtering



Model

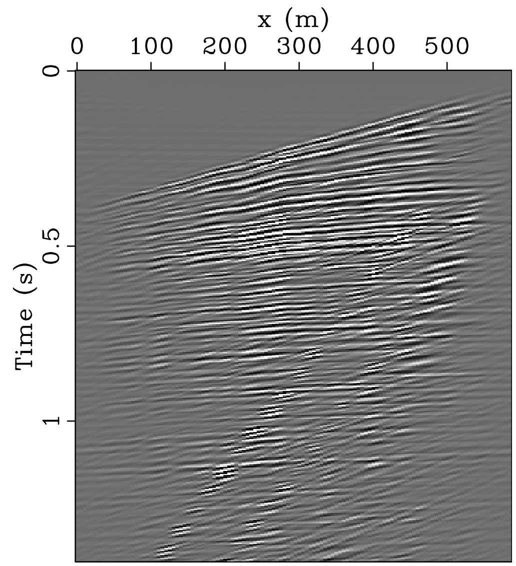


Experiment 3



model
(5 m)

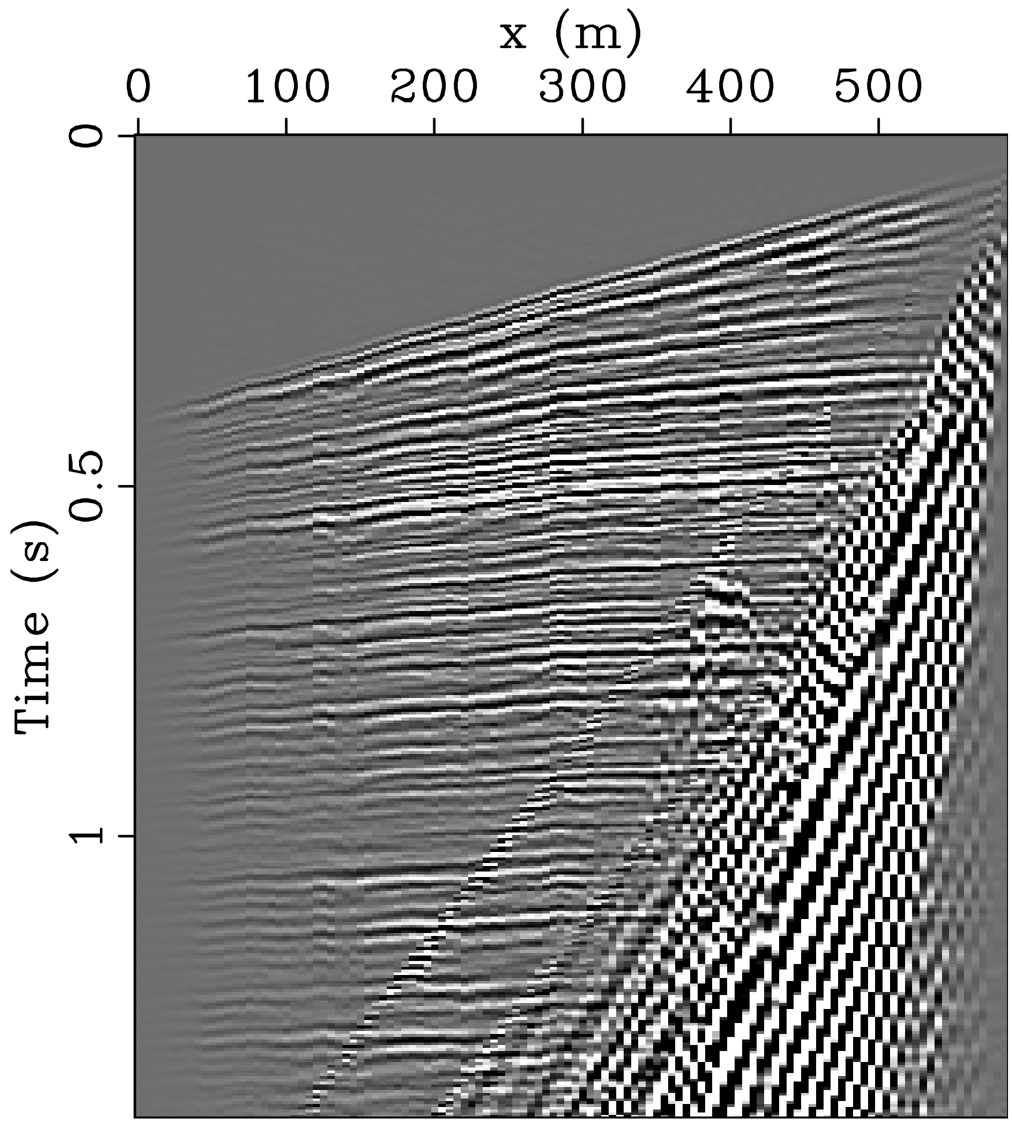
CRSI +
FK filtering



filtered interpolated
result
(1 m)

reproducible figure(s)*

Model: 5 m



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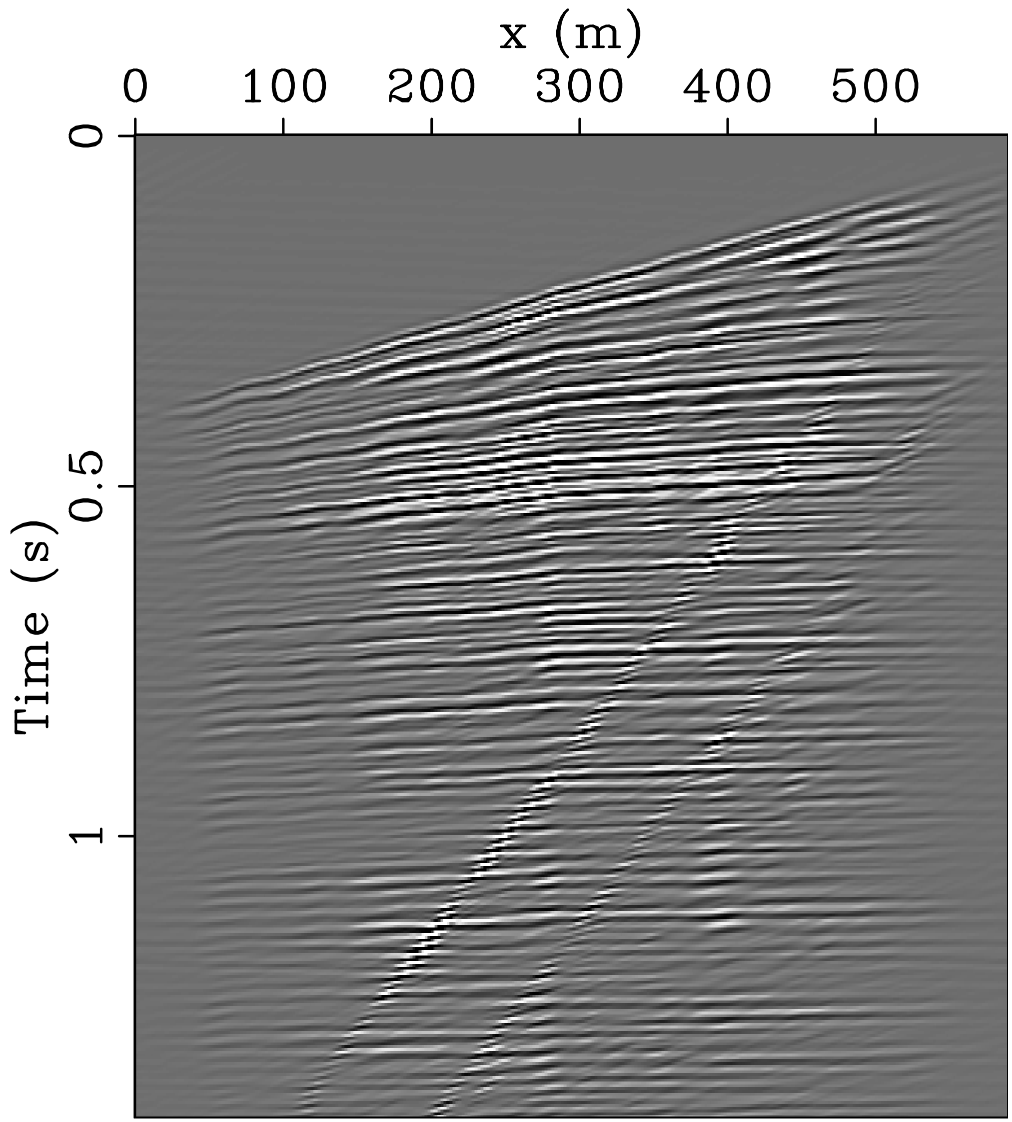
CRSI combined with FK filtering: 1m



Conclusions

- **curvelets** exploit the very strong geometrical structure of seismic data
- **sparsity** & **stable signal recovery theory** provide robust sampling criteria (in progress)
- **CRSI** performs well
  - synthetic 1: “data from hell”
    - SLIMpy demo works(!)
    - CRSI performs well even in the challenging case of regularly missing traces
  - synthetic 2: Delphi’s primary-multiple dataset
    - CRSI outperforms FRSI & PWD
    - significant uplift from 2D to 3D
  - real 1: Gippsland
    - from 180 m to 12.5 m
  - real 2: Friendswood
    - CRSI interpolates both signal & noise (i.e. ground roll)
    - CRSI can also remove noise as part of the interpolation
    - from 20 m to 2.5 m

Future work

- assess CRSI's performance based on
  - ground roll removal
  - multiple prediction and removal
- implementation
  - **fast** **large-scale** **sparsity-enhancing** solver
- theory
  - robust sampling criteria
  - is there an "optimal" sparse sampling scheme?
- interpolation of truly irregularly sampled data
  - Nonuniform Fast Discrete Curvelet Transform (NFDCT) - the "seismic curvelets" (this afternoon 4:15 pm)
  - CRSI with NFDCT

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