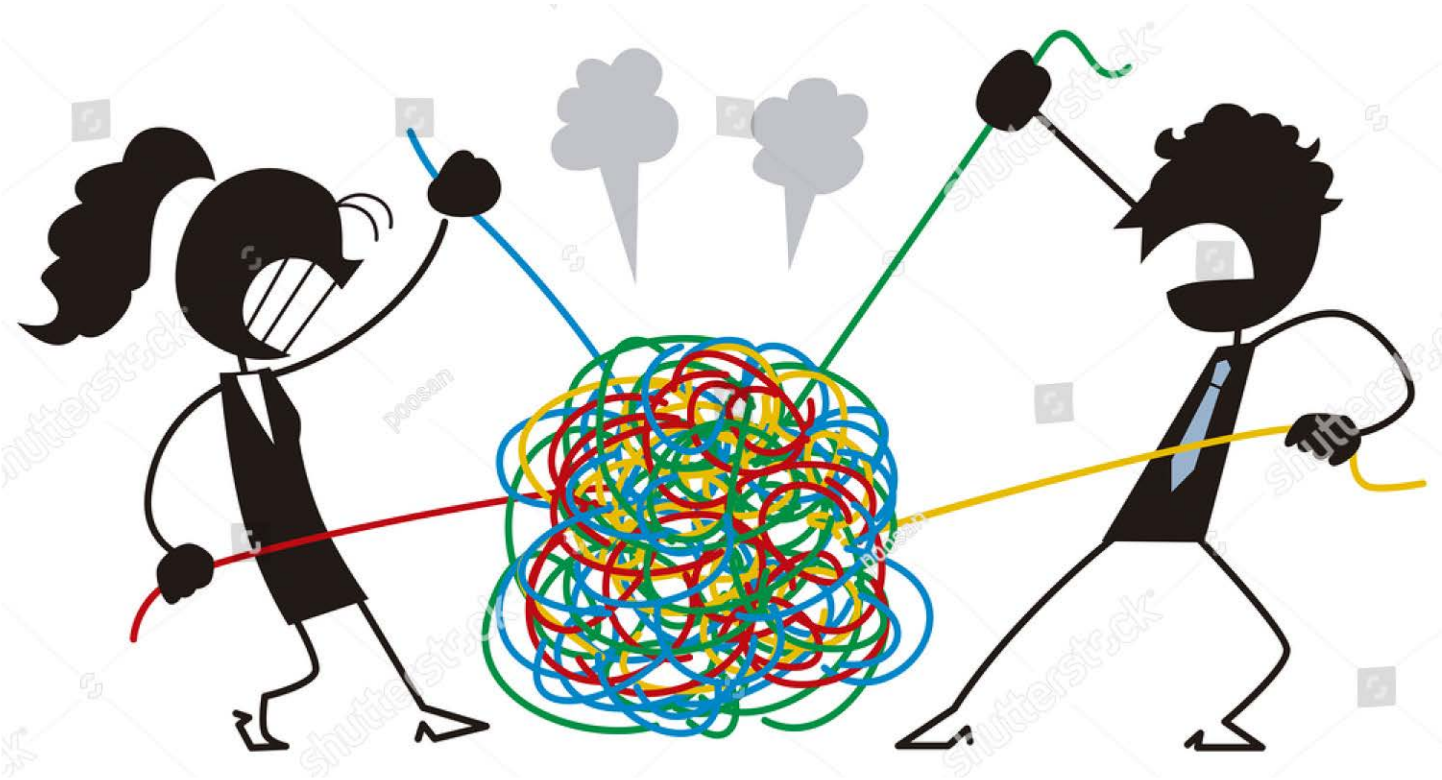
DATA DEBLENDING (in many flavours)

Daniel Trad



NSERC CRSNG
UNIVERSITY OF CALGARY
FACULTY OF SCIENCE
Department of Geoscience

DATA DEBLENDING CREWES GROUP

Daniel Trad

Madagascar Package (this talk)

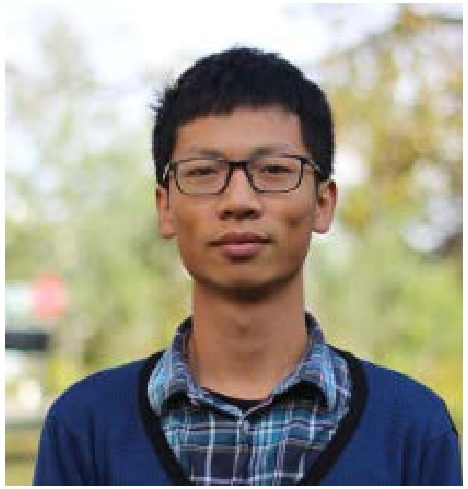
Amr Ibrahim

Postdoc (real data)

Kai Zhuang

PhD 3D deblending

Ziguang Su



PhD- Nodes

Zhan Niu

Theory Guided Machine Learning

Deblending Package (C++) (OOP Modules)

Madagascar

sfsynthfd (MPI) → Synthetic blended data

sflsprtm (MPI) → LSRTM (blended-deblended)

sfdeblending (MPI)→Deblending via Time Domain Radon

sflsdeblending→LSDeblending via TD Radon.

sflskirchhoff → Kirchhoff time migration

Seismic Unix (to be ported to Madagascar soon):

suradonhybrid

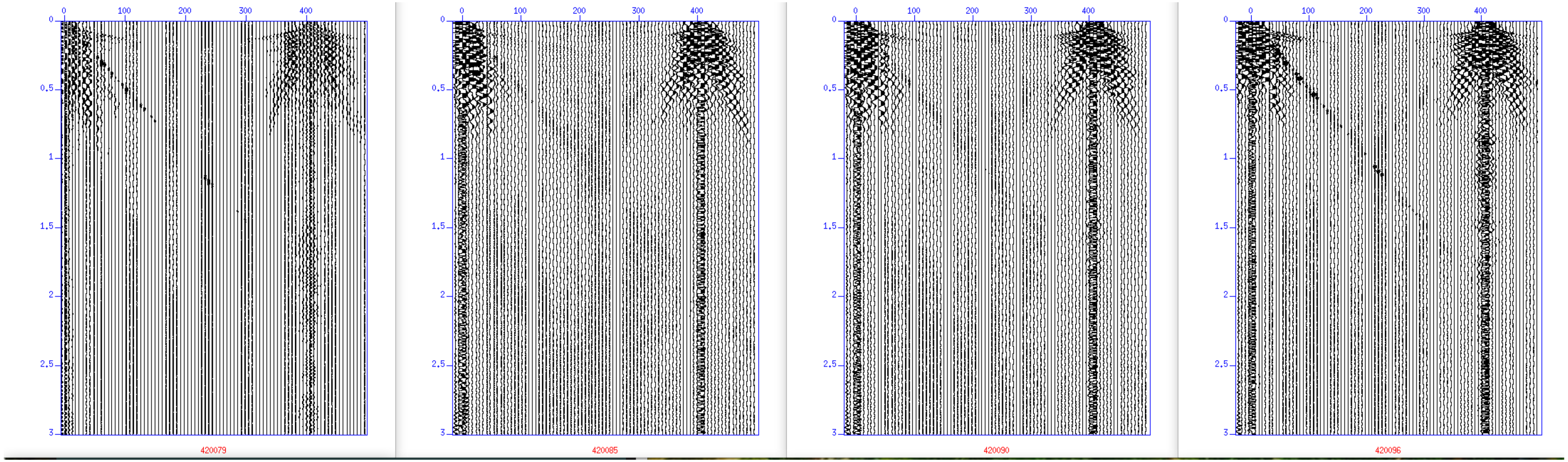
sustolt

Available upon request and patience

The benefit and challenge of blended acquisitions

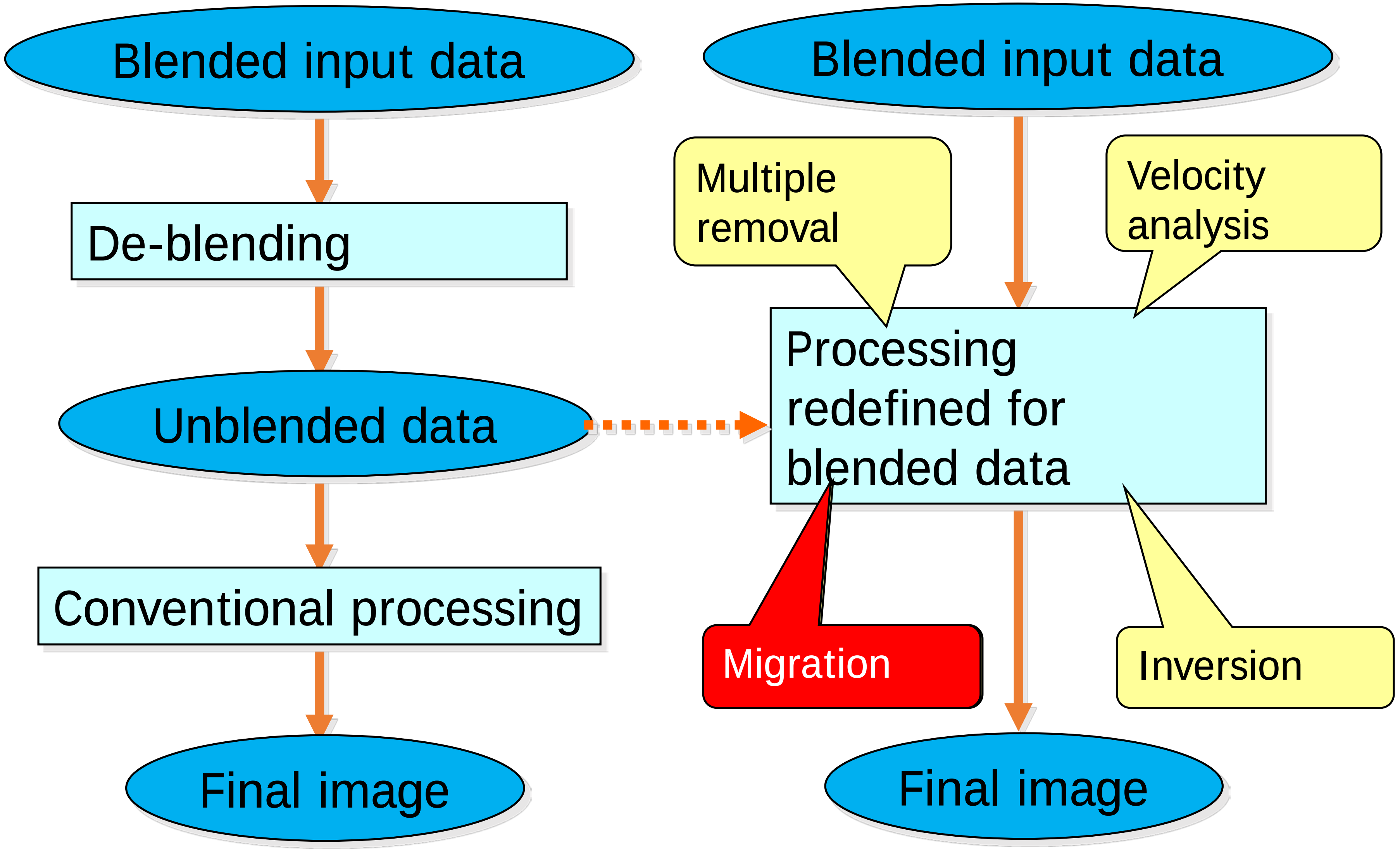
Blended acquisitions allow to increase the **illumination** for the same **shot density** by maintaining the **acquisition cost** reasonable

Processing of blended data is **challenging,** each trace contains information from different sources, each trace has many offsets and azimuths



CREWES data set acquired in 2018

Deblending Processing (Verschuur, 2011)



Different deblending approaches

Pseudodeblending + noise attenuation

Multidimensional inversion of pseudo-deblended transform

Physical transformations

Geometry

Blender

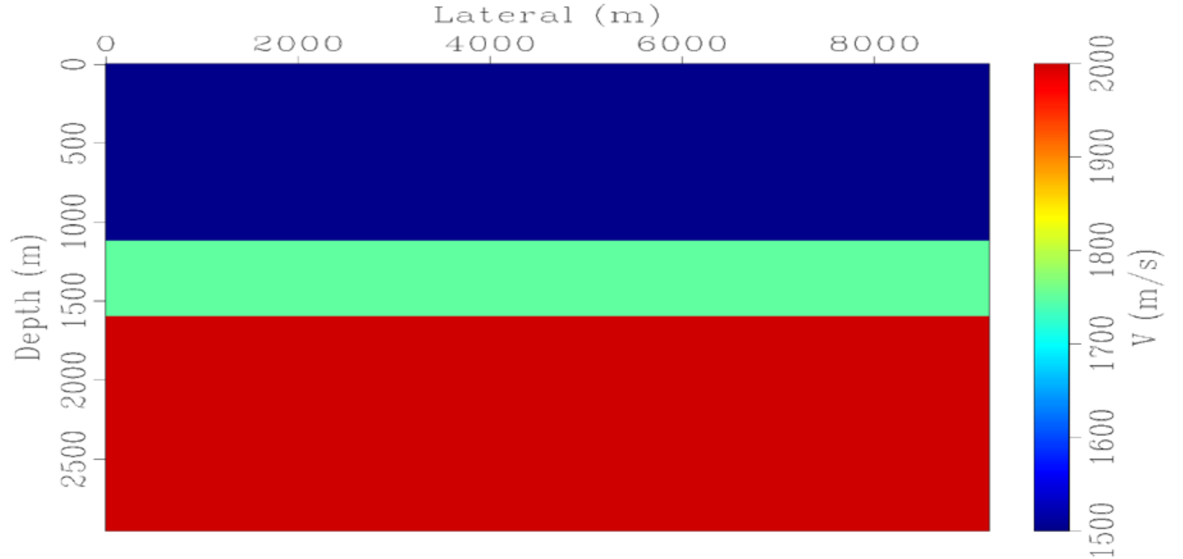
Transform

Conjugate Gradient

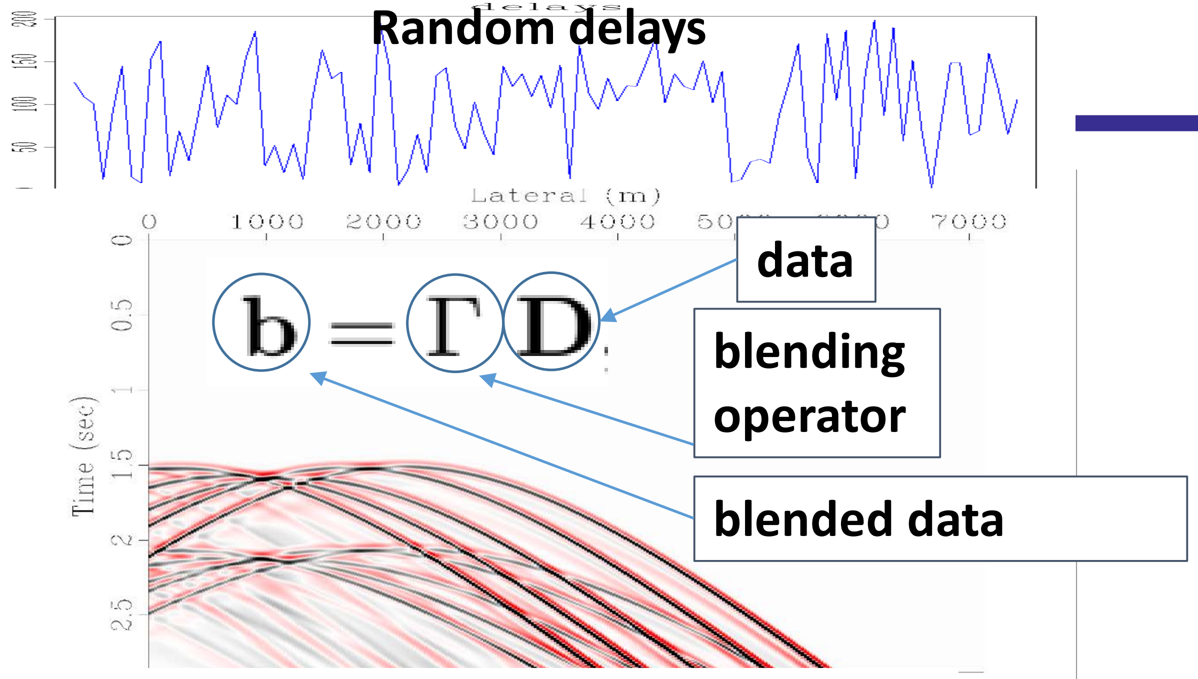
classes

Object Oriented Programming

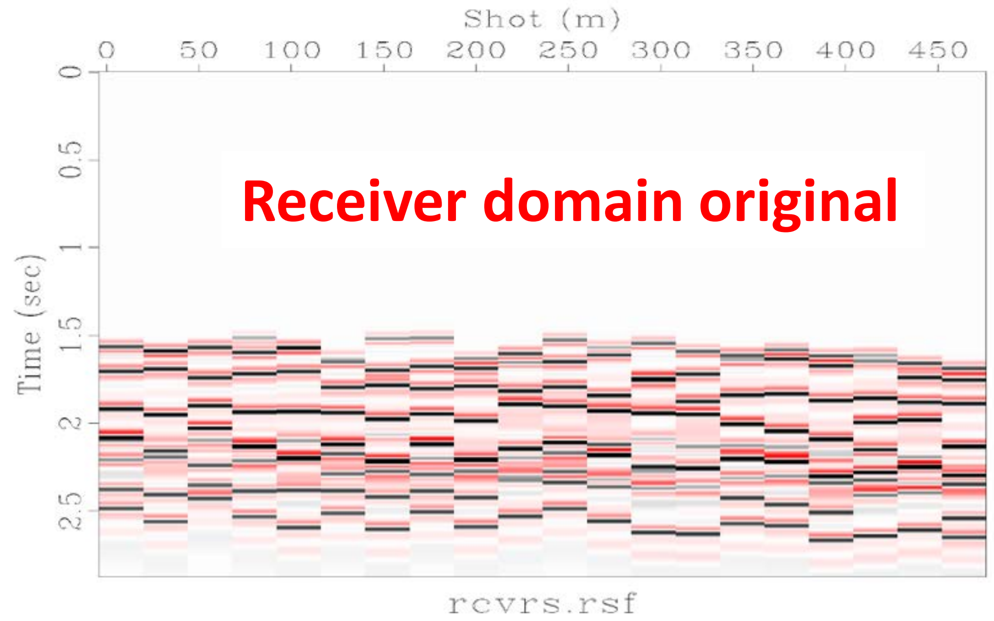
Pseudo-Deblending



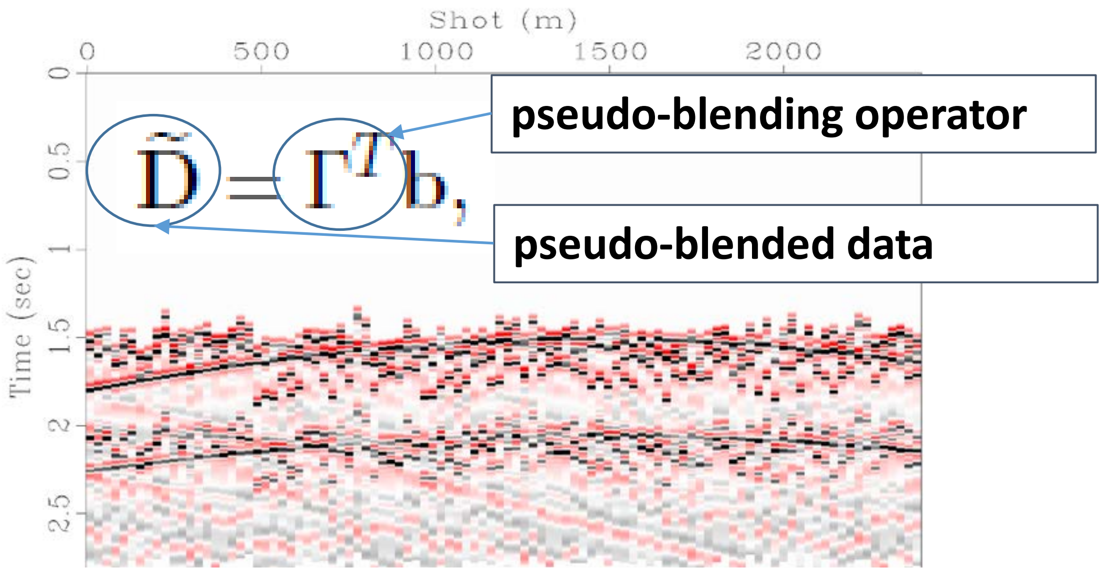
velocity



supershot with shooting delays



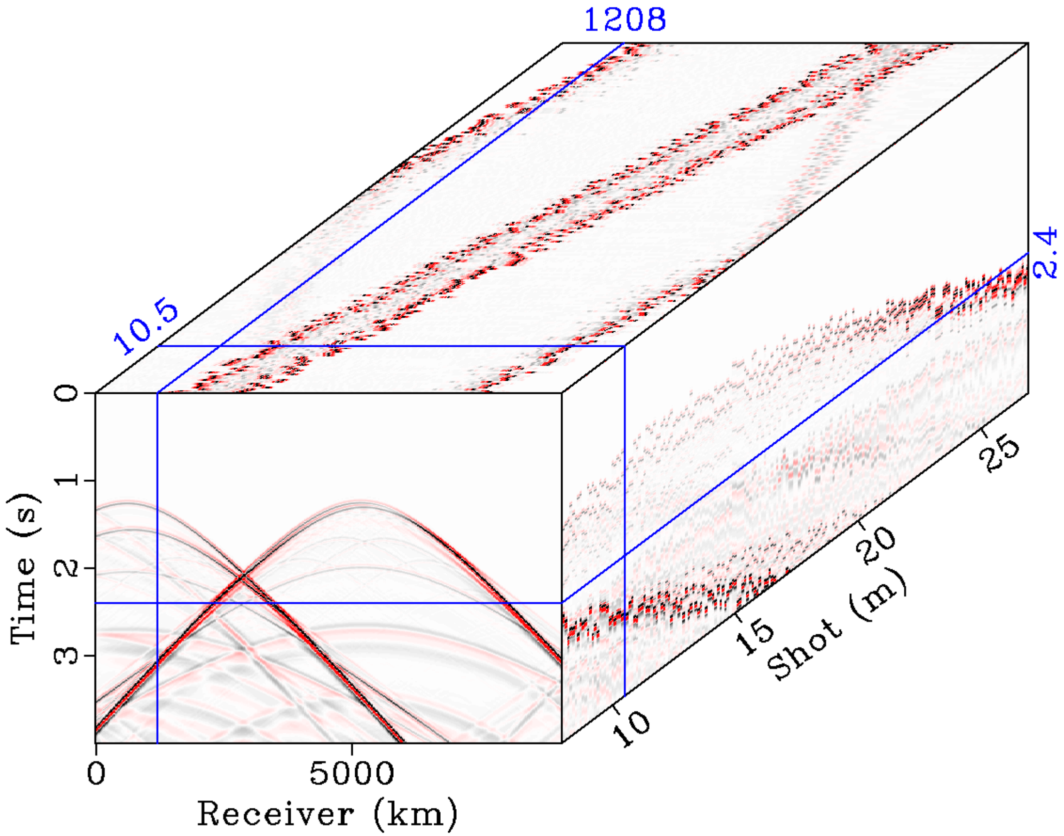
Receiver domain original



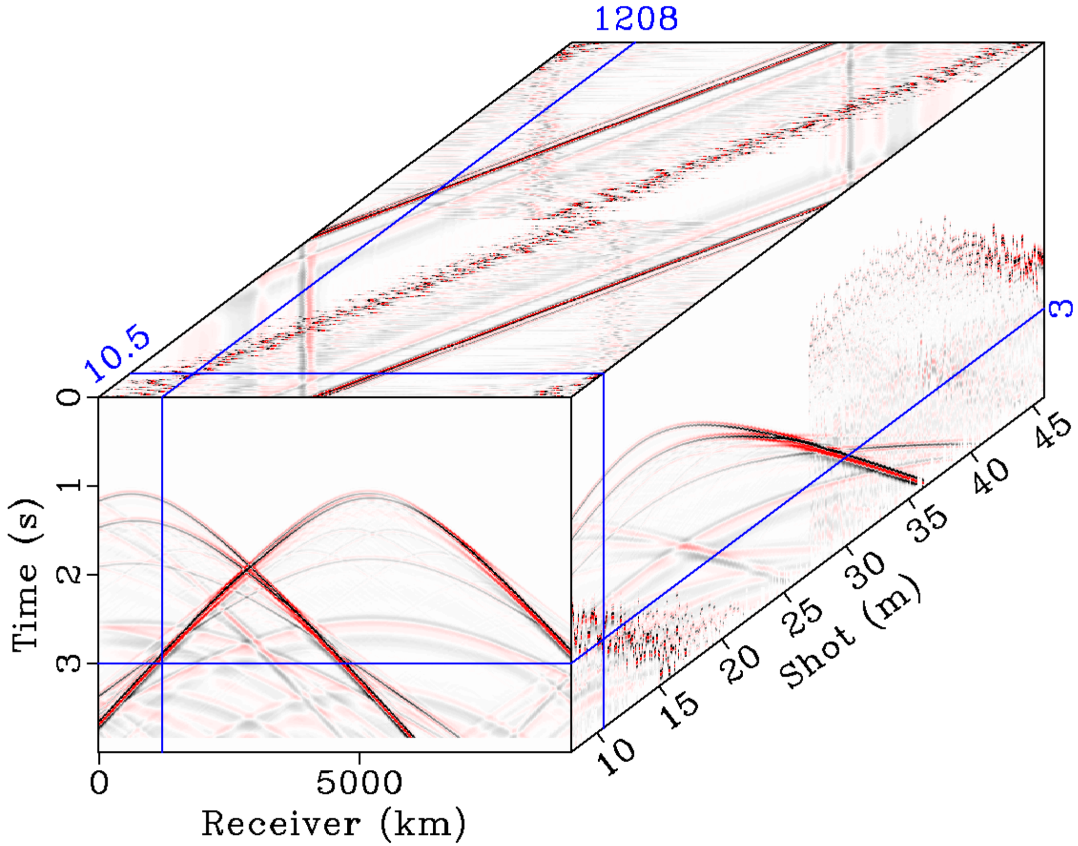
Receiver domain after pseudo-deblending

Pseudo-deblending with time dithering

Blended Data

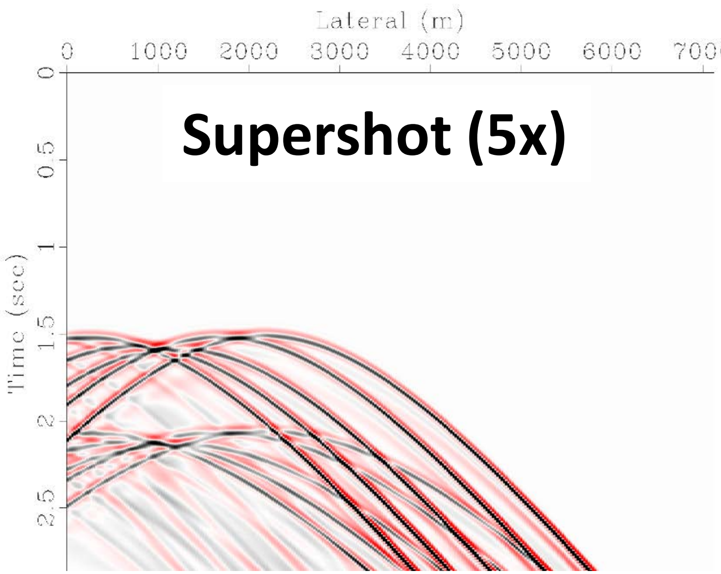


Pseudo Deblended Data

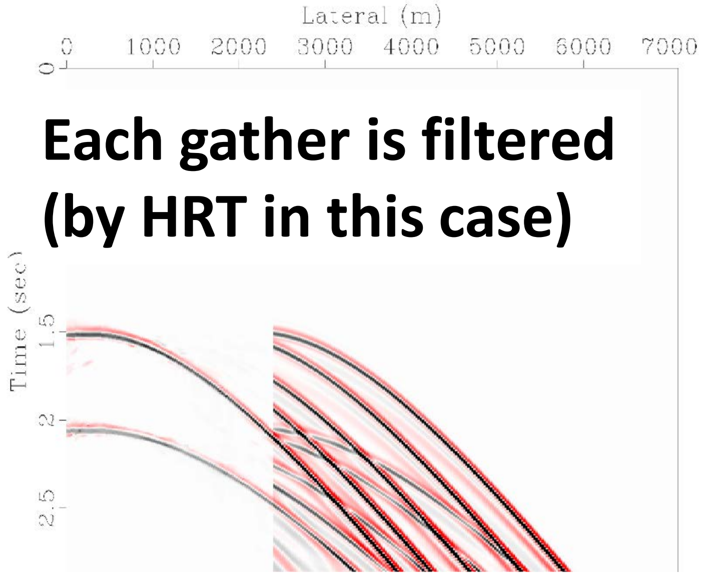


From Kai Zhuang

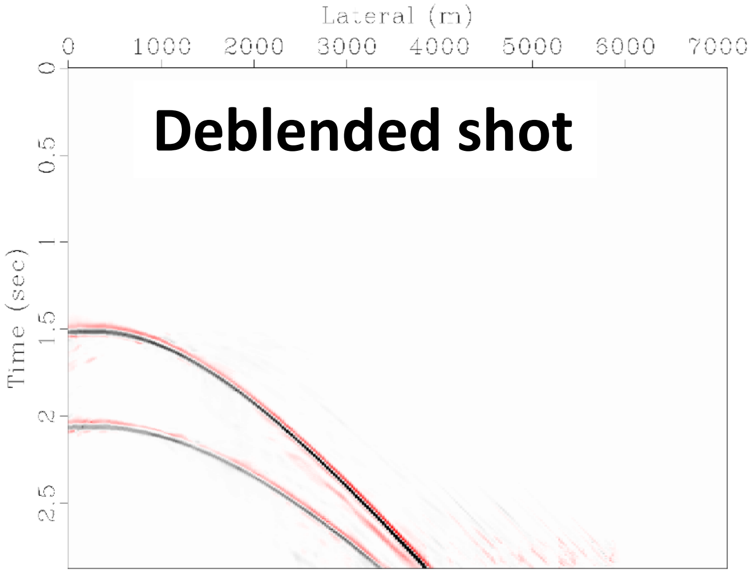
Deblending by filtering in receiver gathers (Hres Radon Transform)



original blended



One third of receiver gathers filtered



All receiver gathers filtered

p = 2 Robust data fitting

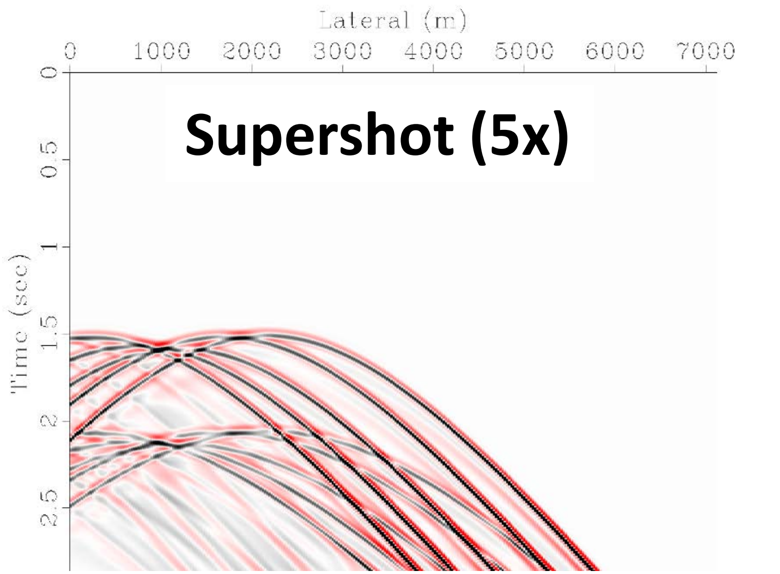
q = 1 Sparse transform

$$J = \|\tilde{\mathrm{D}} - \mathrm{L}\,\mathrm{m}\|_p^p + \mu \|\mathrm{m}\|_q^q,$$

Individual inversion on each rcvr gather

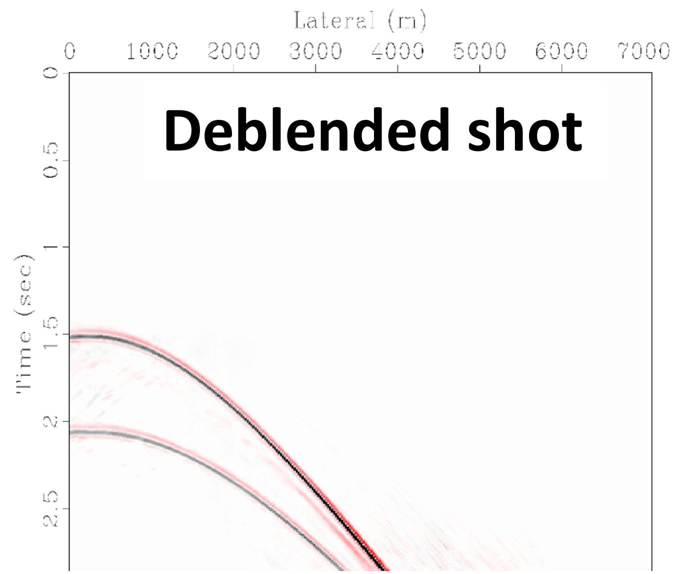
Increasing number of receiver gathers being filtered

Deblending by LS inversion in receiver gathers (Hres Radon Transform)



original blended

Blended data fitted
by simultaneous models.
Deblending occurs by
predicting blended shots
from individual models



All receiver gathers filtered

p = 2 Least squares data fitting

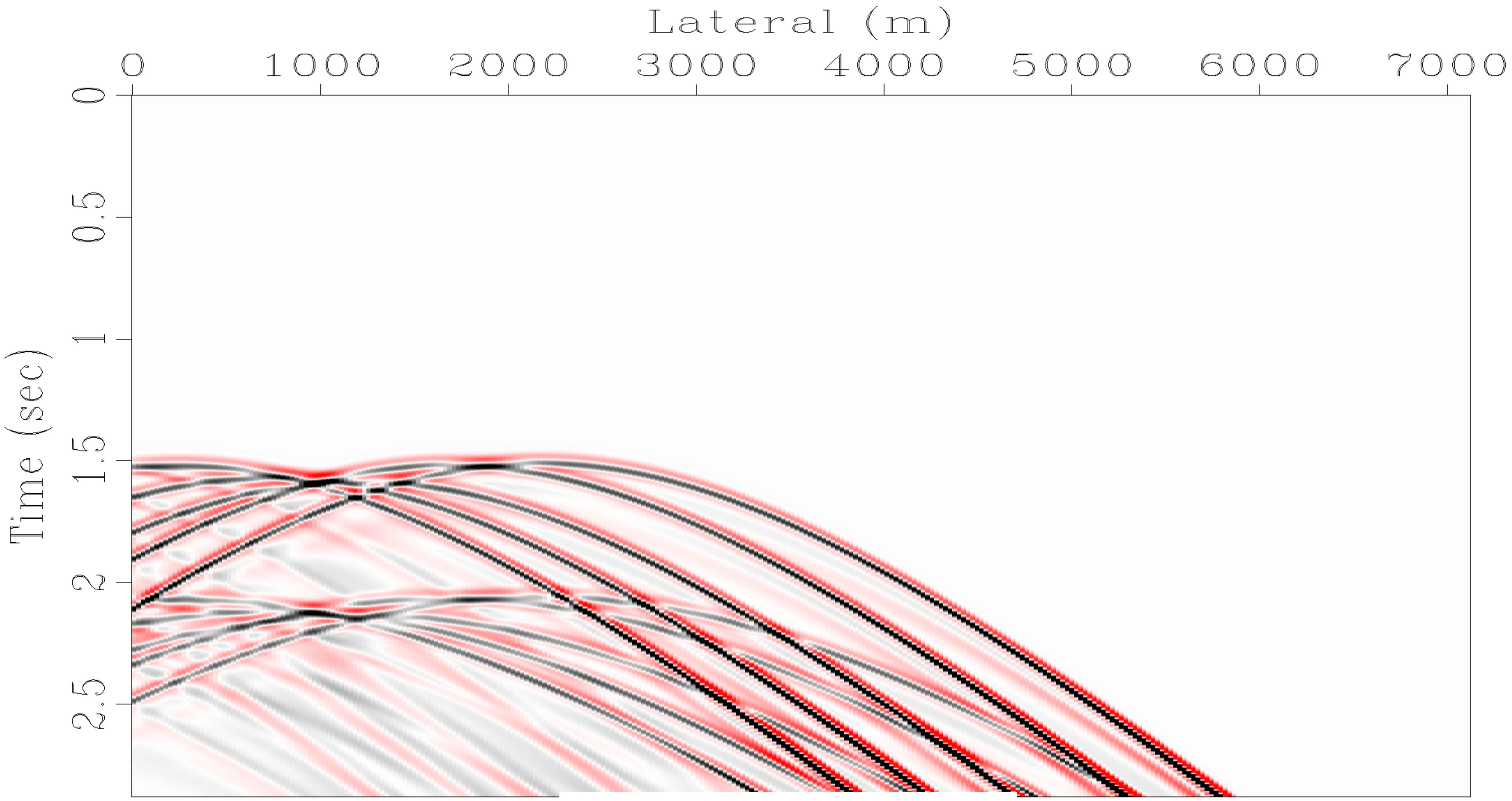
q = 1 Sparse transform

$$J = \|\mathrm{b} - \Gamma L \mathrm{m}\|_2^2 + \mu \|\mathrm{m}\|_1^1,$$

Simultaneous inversion of
all blended data

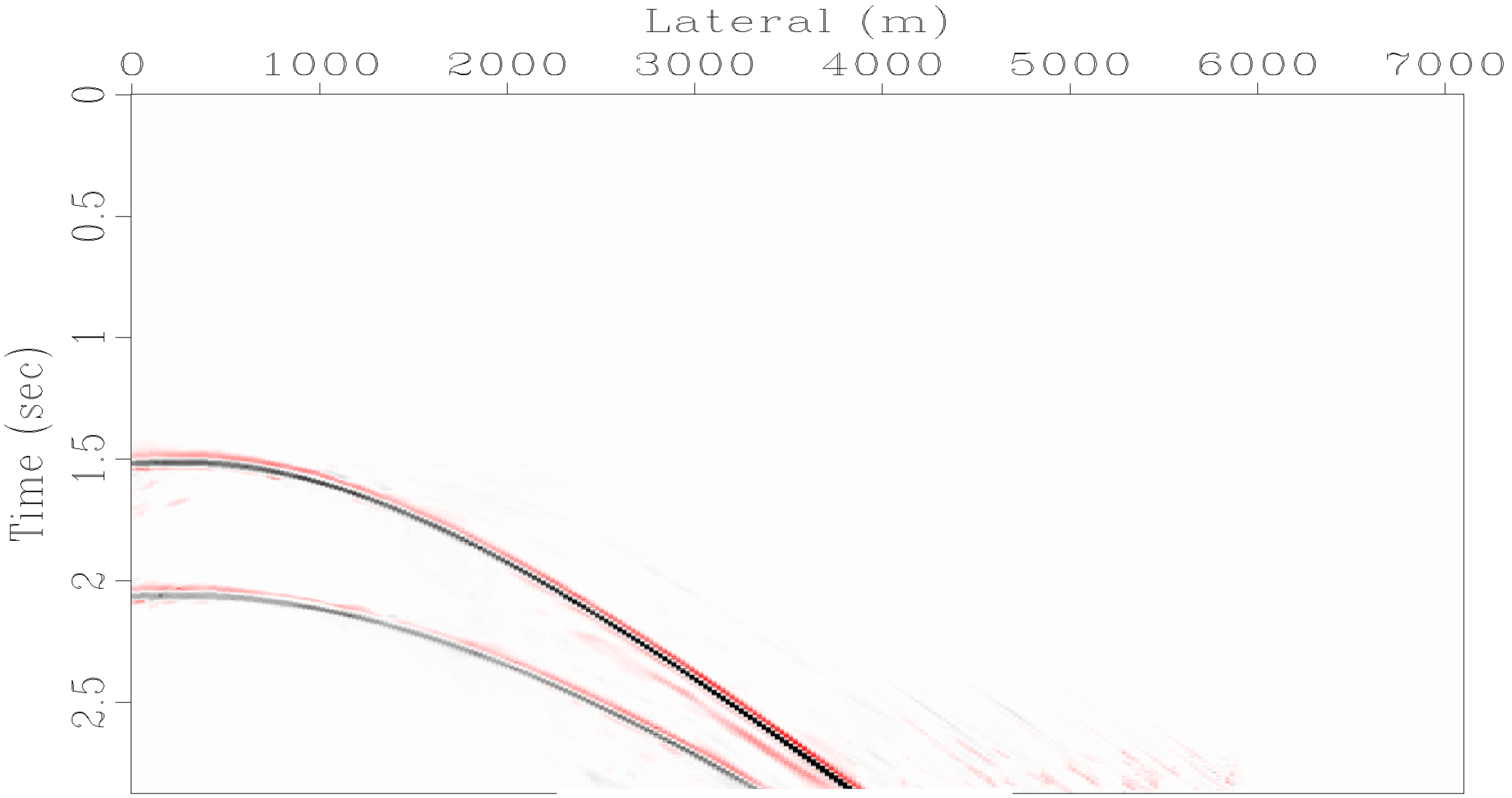
All receiver gathers deblended at once

Supershot modelled by sfsynthfd



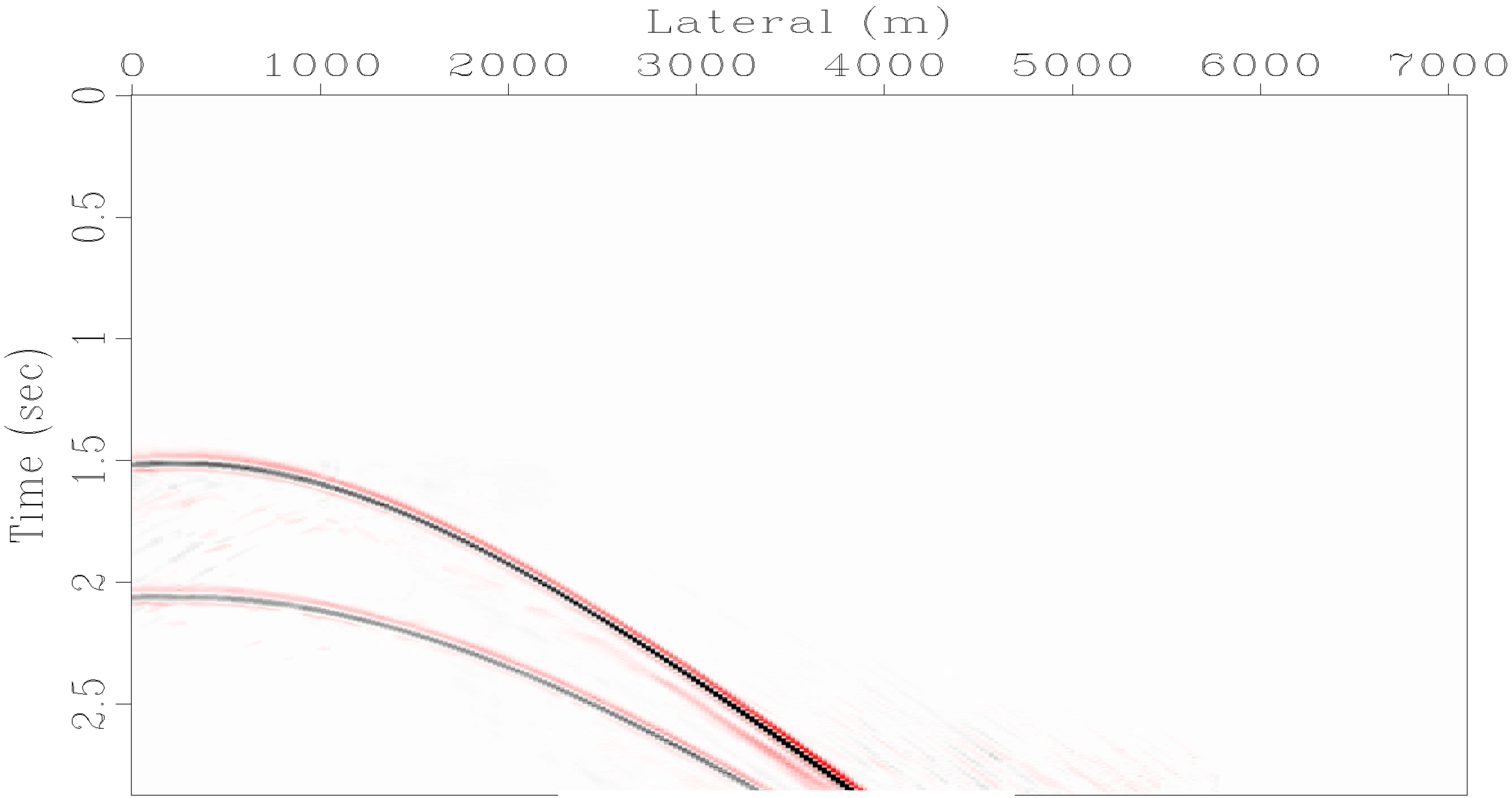
Supershot # 1

Shot after denosing (sfdeblending)

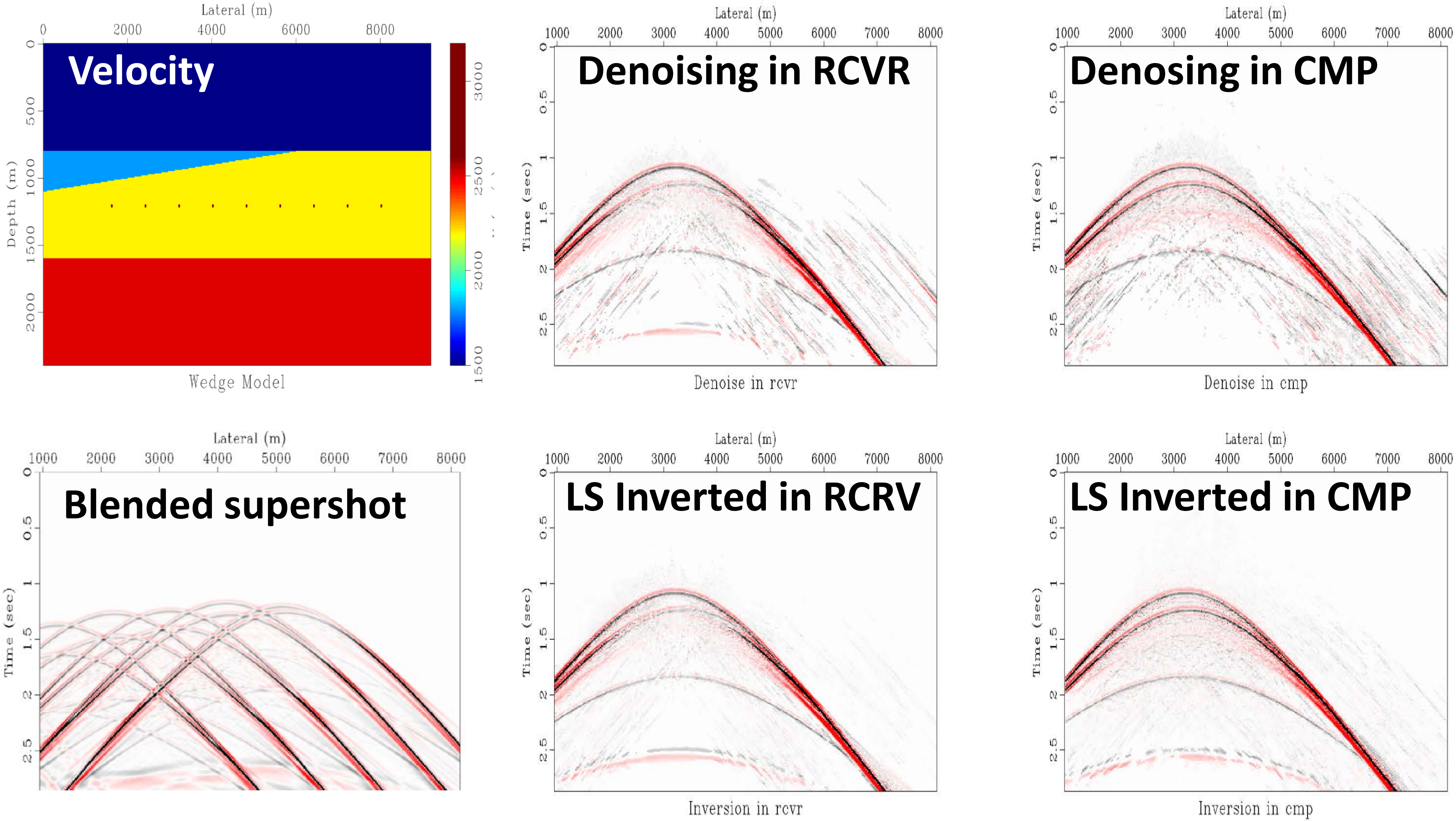


Shot # 1

Shot after LS inversion (sflsdeblending)

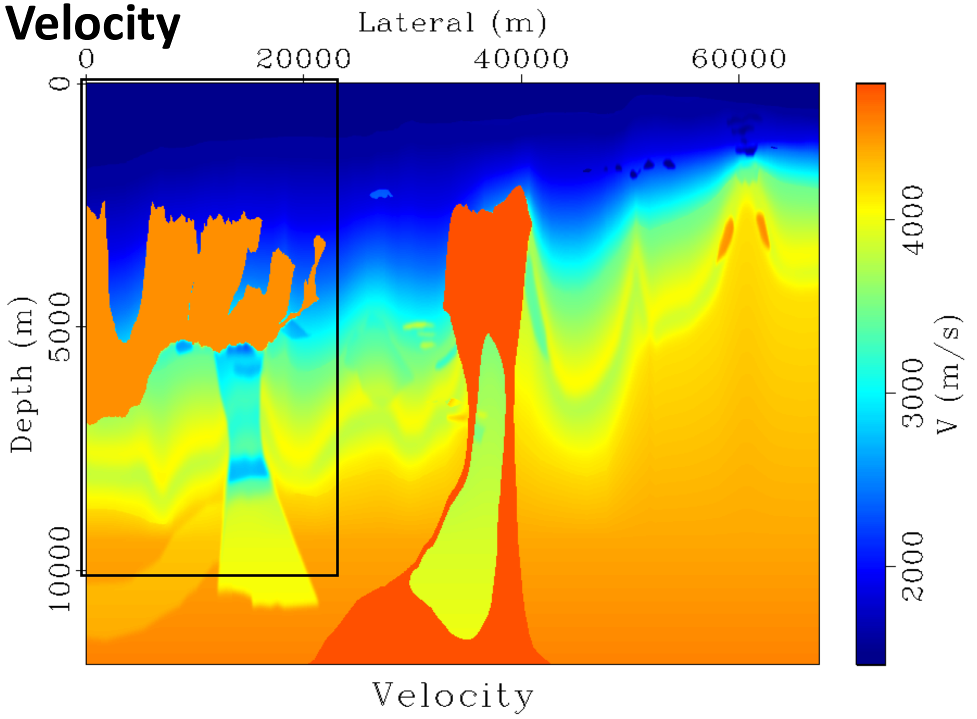


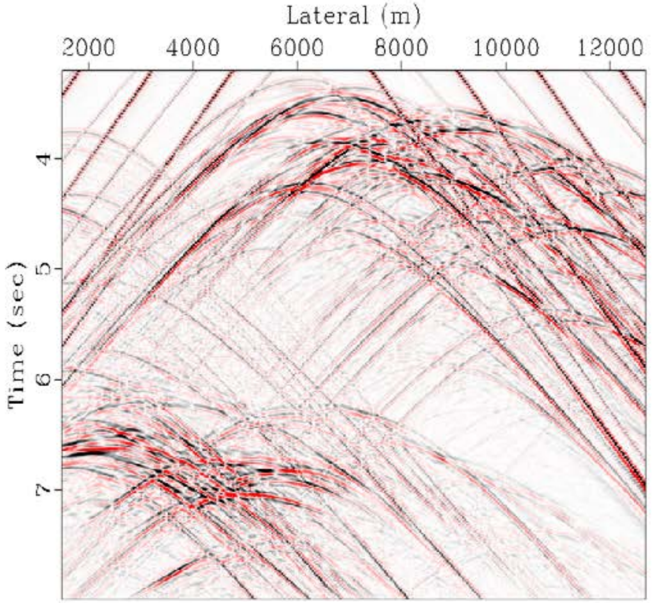
Shot # 1



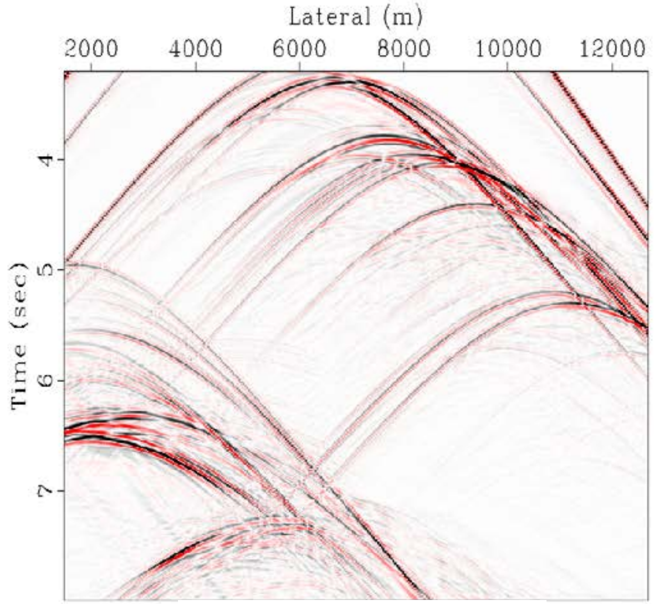
Velocity
Lateral (m)
0
2000
4000
6000
8000
Depth (m)
500
1000
1500
2000
3000
2500
2000
1500
Wedge Model
Denoising in RCVR
Lateral (m)
1000
2000
3000
4000
5000
6000
7000
8000
Time (sec)
0
0.5
1
1.5
2
2.5
Denoise in rcvr
Denosing in CMP
Denoise in cmp
Blended supershot
LS Inverted in RCRV
Inversion in rcvr
LS Inverted in CMP
Inversion in cmp

Velocity

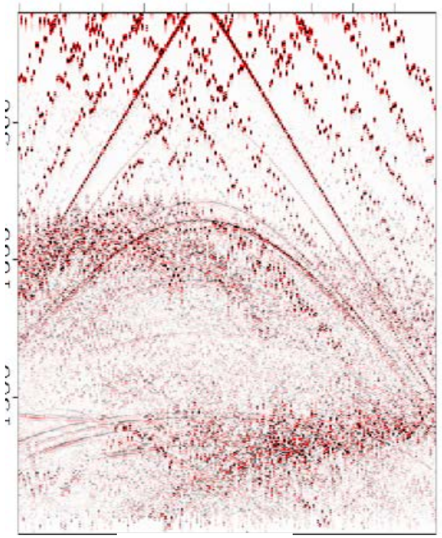




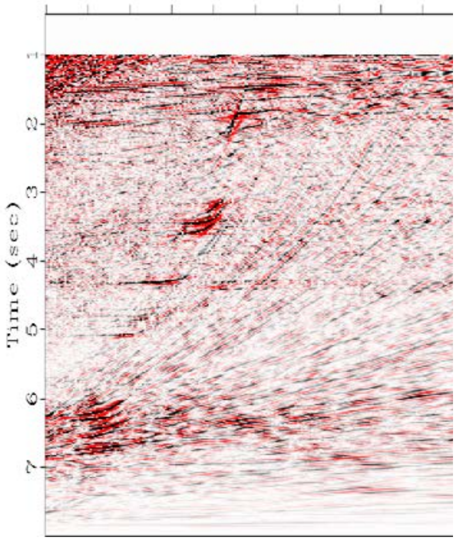
Supershot (5x)



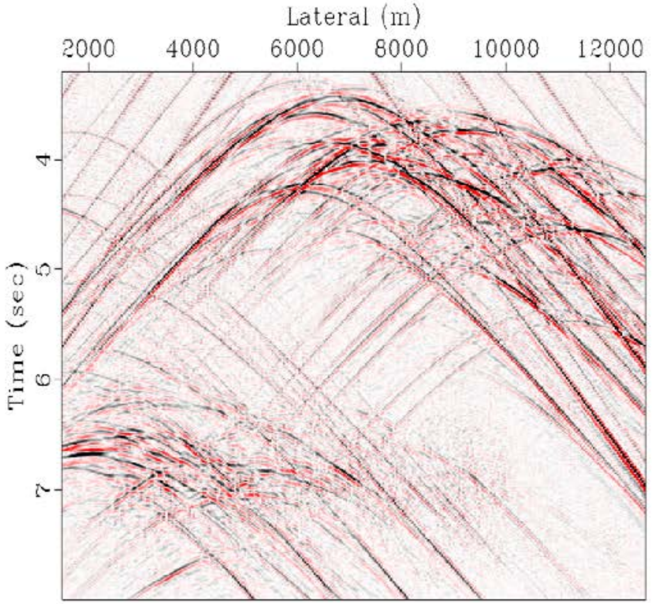
Never Blended



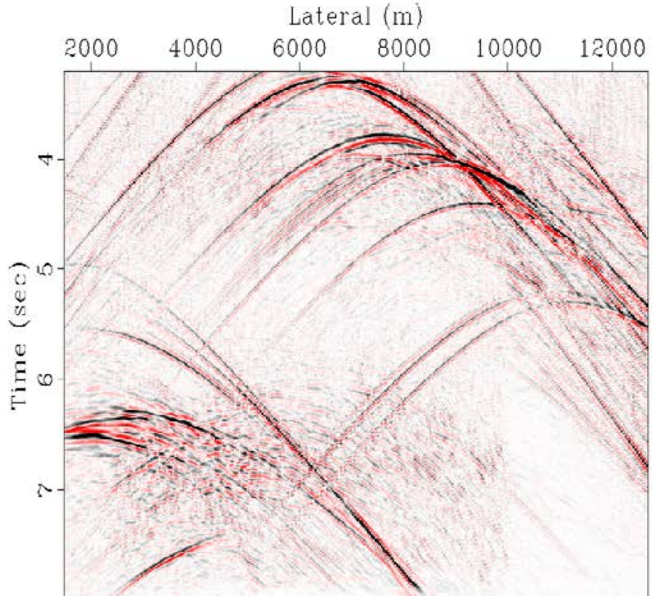
CMP



Radon

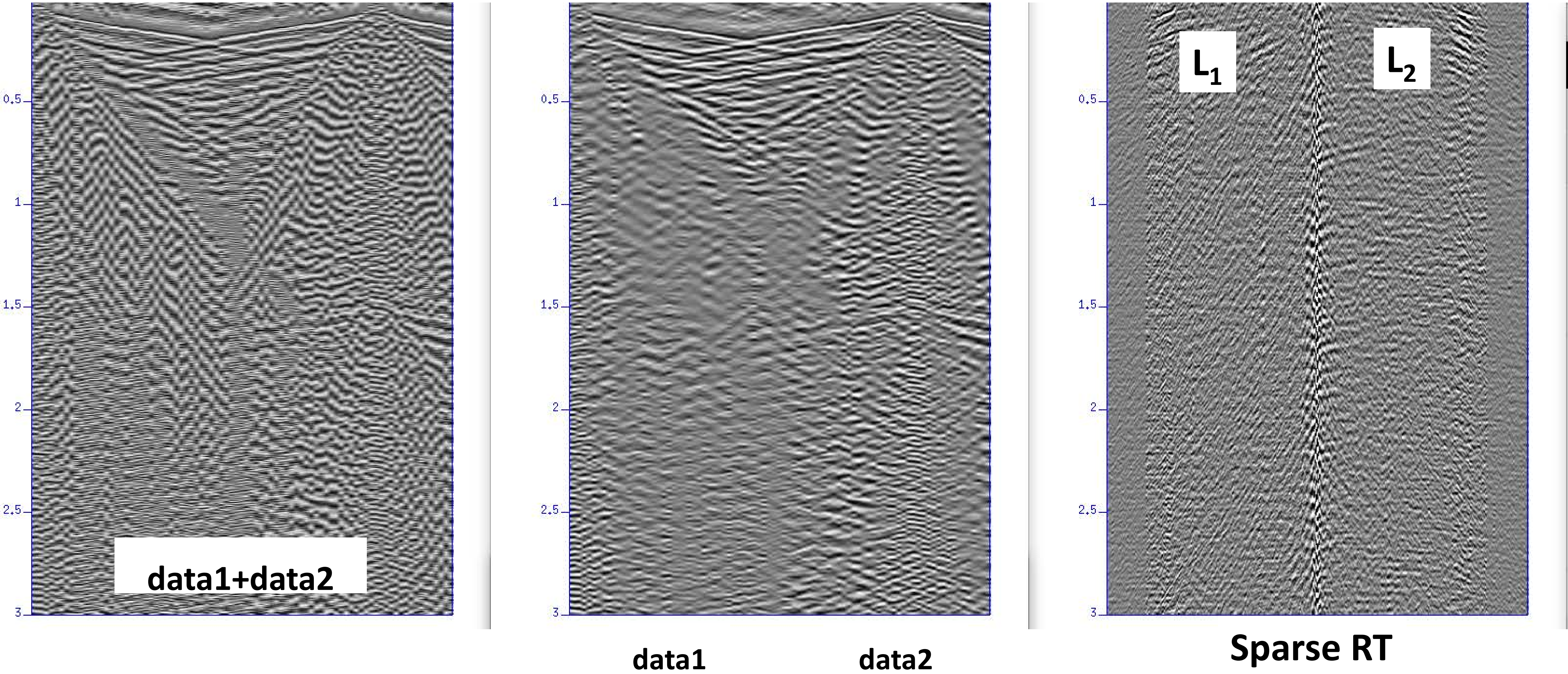


Predicted Blended data

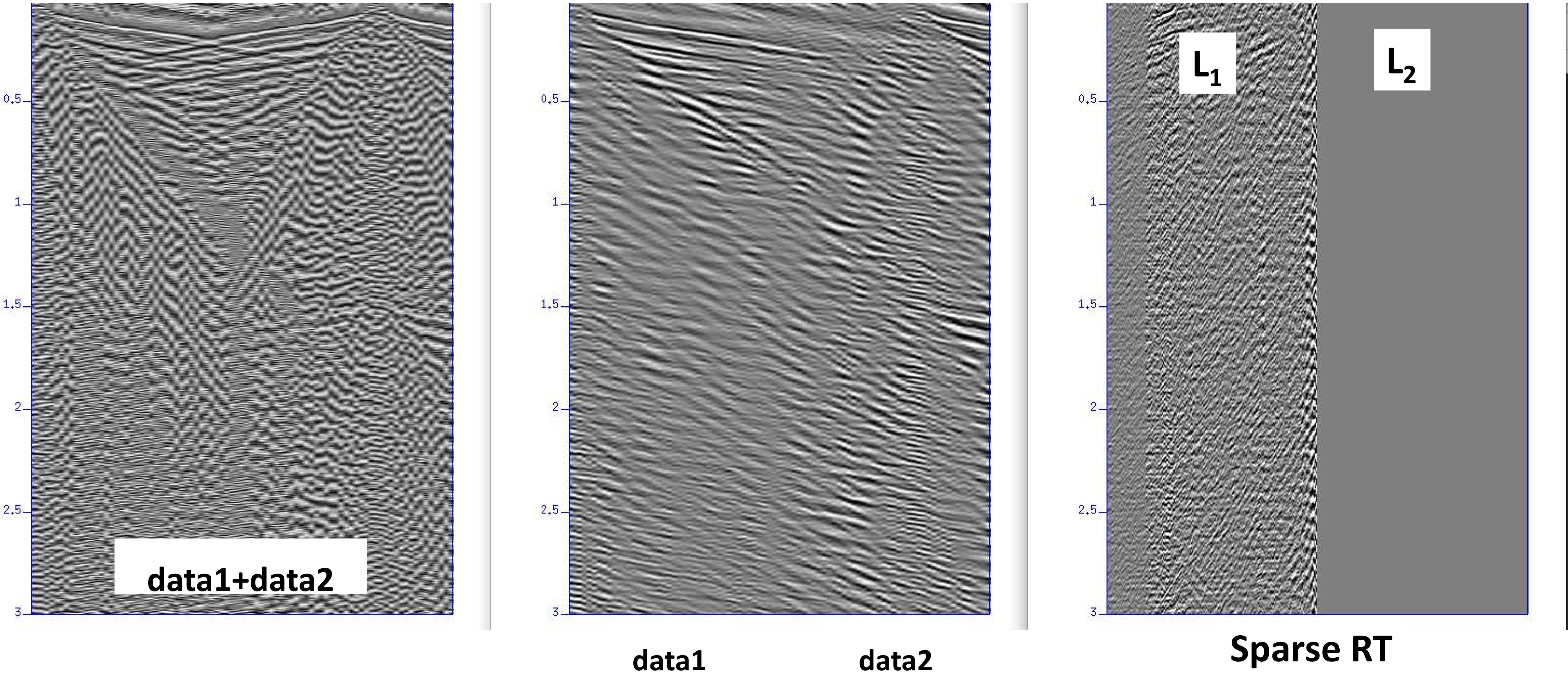


Predicted deblended data

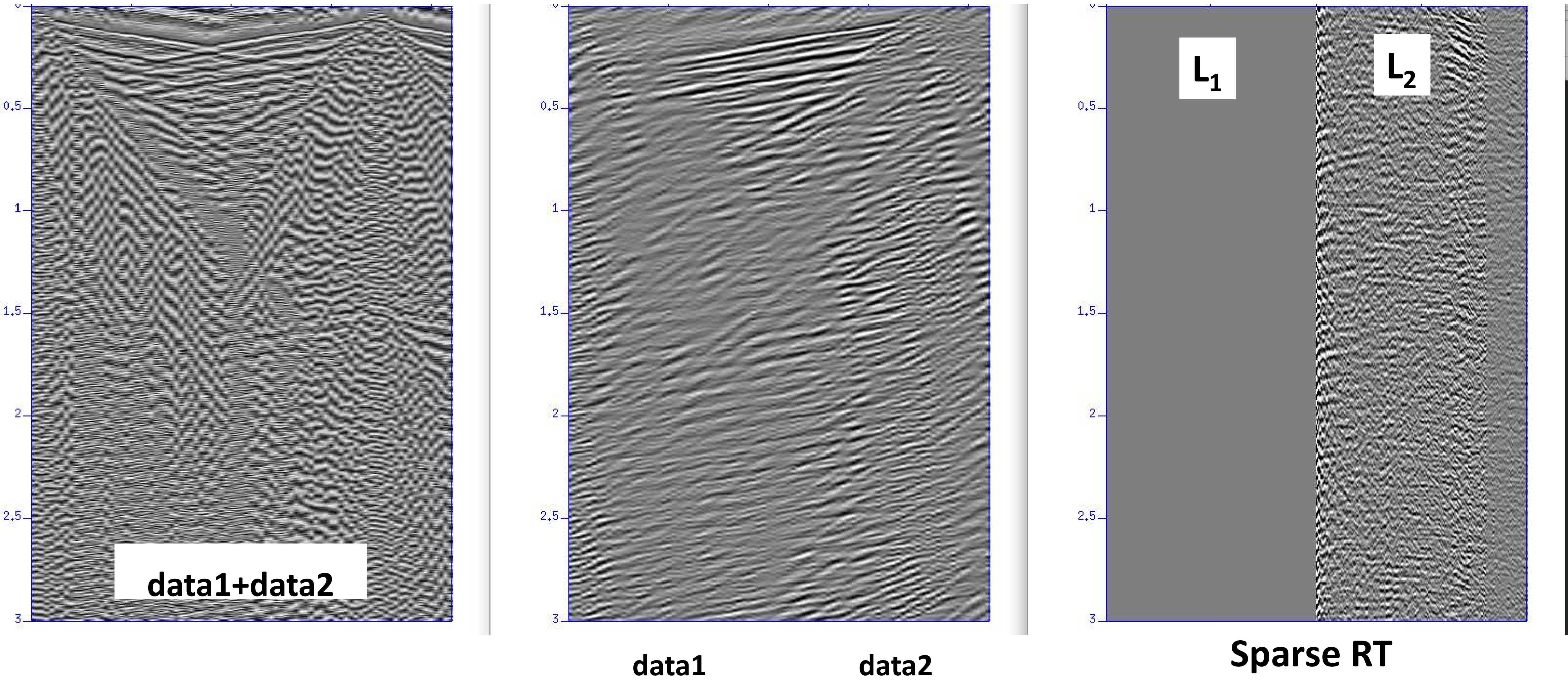
CREWES field record deblending without time dithering



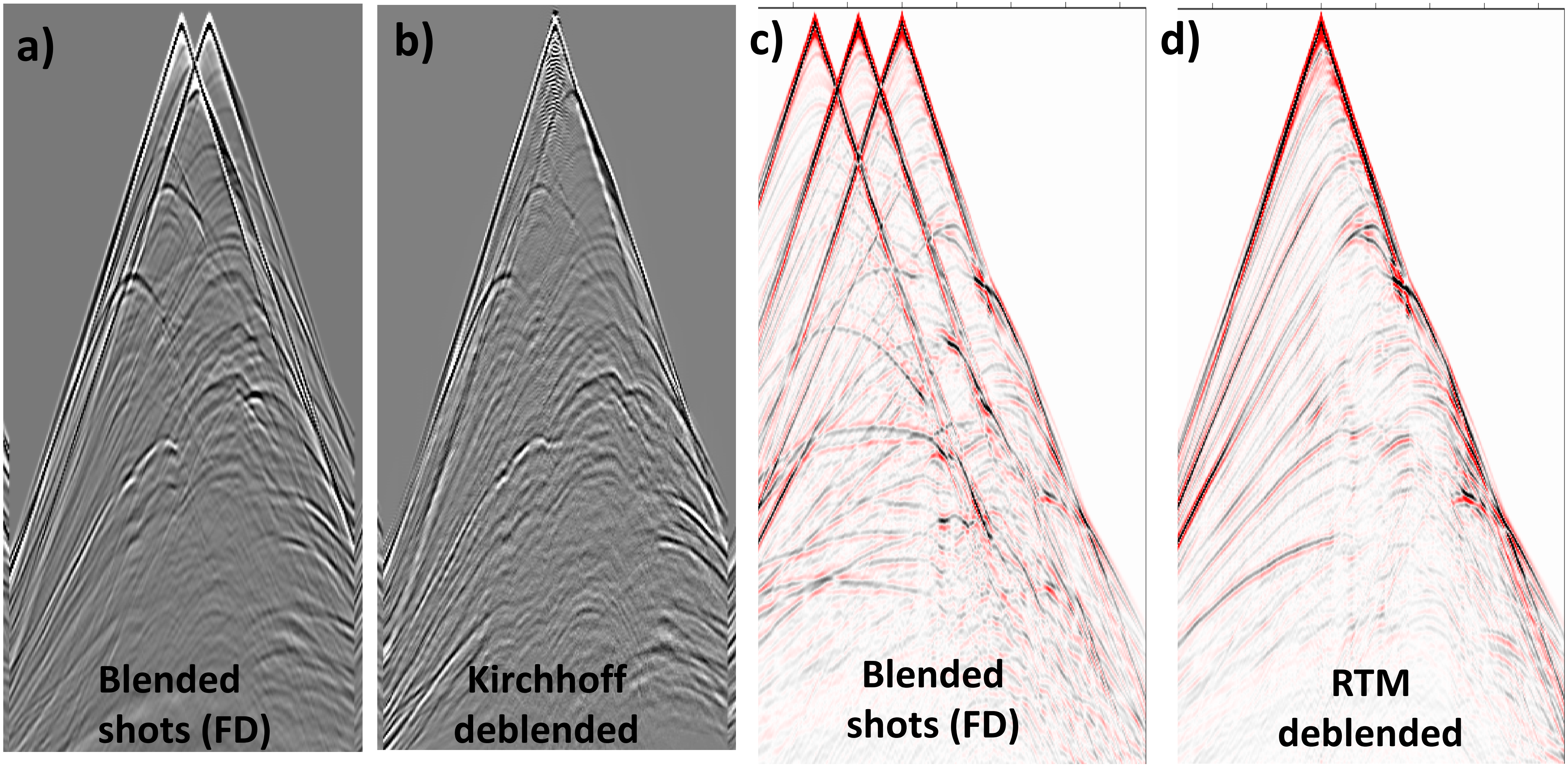
CREWES field record deblending without time dithering



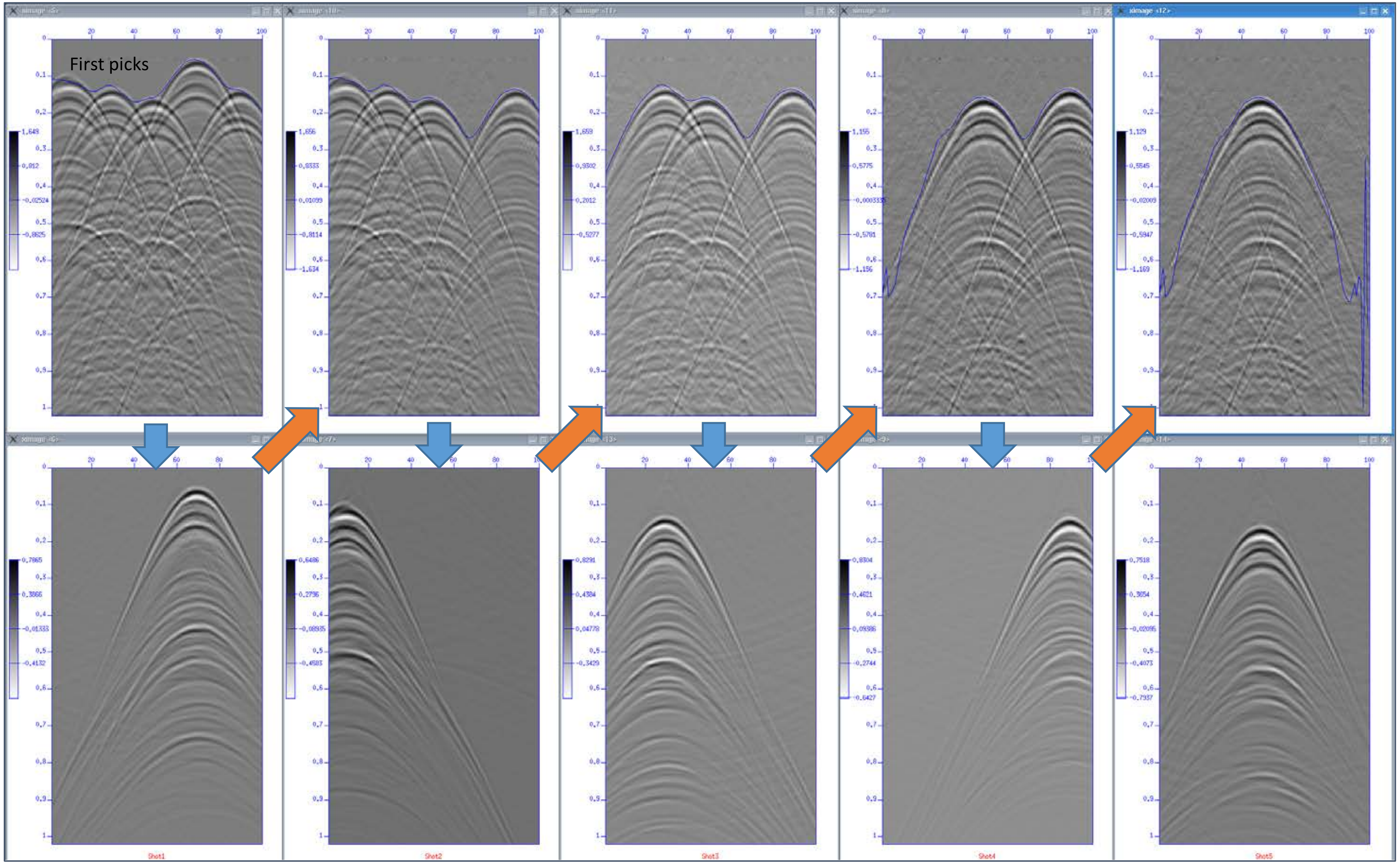
CREWES field record deblending without time dithering



Deblended shots with migration/demigration



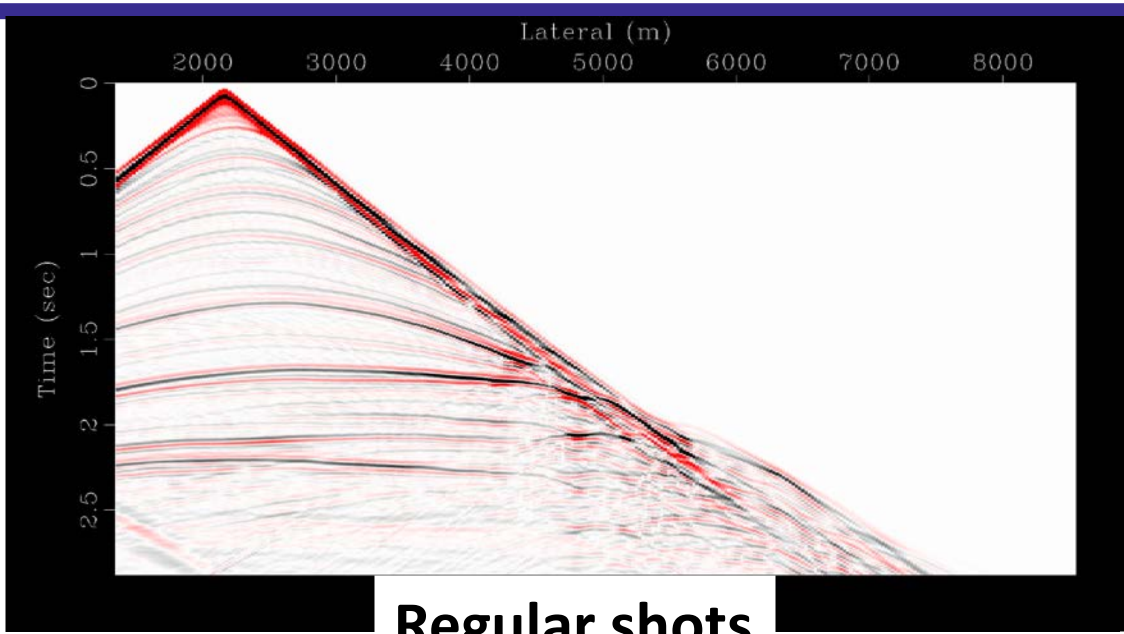
Stolt Apex shifted Radon transform deblending (Trad, 2003, 2012)



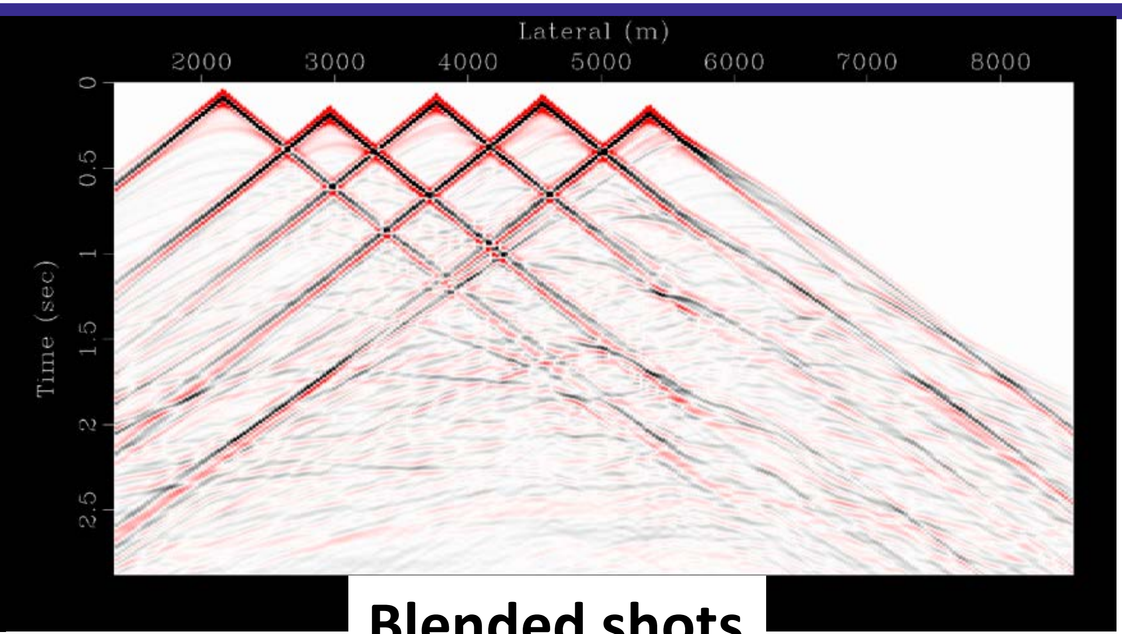
Apex Shifted Radon Transform

Subtraction (no adaptive yet)

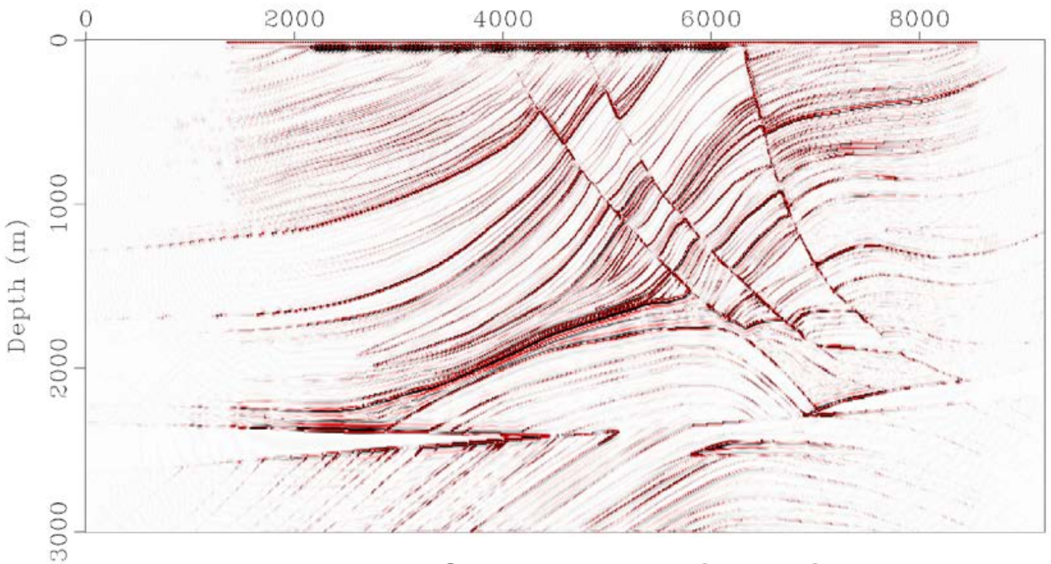
Imaging blended data directly



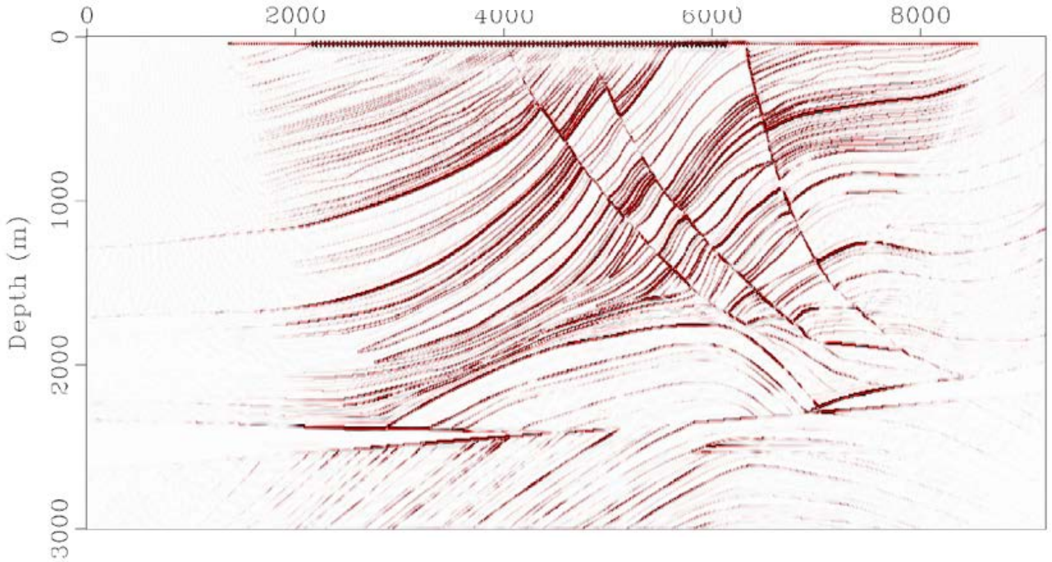
Regular shots



Blended shots



RTM from regular shots



LSRTM from blended shots

Conclusions

- Presented different deblending approaches:
  - *LS denosing*
  - *LS inversion*
  - *LS migration*
- OOP approach: different combinations of a few different classes (LEGO approach)
- Educational deblending package for deblending in multiple flavours
  - Python Madagascar scripts for dataflow
  - Madagascar API for I/O
  - C++ classes for components and programs

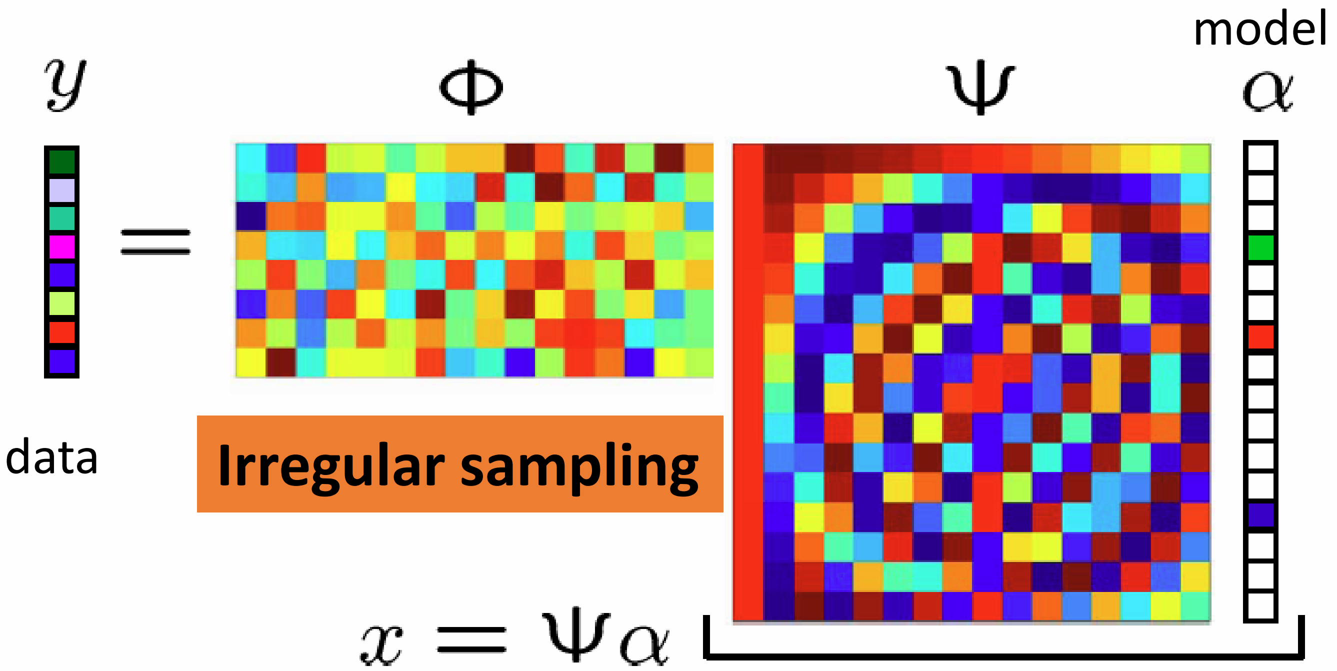
Acknowledgements

- CREWES sponsors
- CSEG
- Natural Science and Engineering Research Council of Canada (NSERC)
- Madagascar (S. Fomel)
- Kai Zhuang, Amr Ibrahim, Sam Gray

Compressive sensing or Compressed sampling

$$y = \Phi x = \Phi \Psi \alpha$$

Compression
+
sampling



synthesis or modeling from sparse transform
(COMPRESSION)

Adapted from Baraniuk, Romberg and Wakin 2008

Compressive sensing or Compressed sampling

$\mathbf{x}$ ➔ unknown

$\mathbf{y} = \mathbf{\Phi x},$ Sampling from regular to irregular sampling

$\mathbf{x} = \mathbf{\Psi}\alpha,$ Transformation to convert from spread out data to dense coefficients

$\text{minimize } \|\mathbf{\Psi^H}_m \mathbf{x}\|_1$ enforce sparseness in the transform coefficients

$\text{subject to } \|\mathbf{\Phi x} - \mathbf{y}\|_2 \leq \sigma$ match the data where sampled

Sparse transforms formulation

$$\mathbf{d} = \mathbf{L}\mathbf{m},$$

Modeling (inverse transform)
data and model can be regular or irregular

$$\text{minimize } \|\mathbf{m}\|_1$$

enforce sparseness in the transform coefficients

$$\text{subject to } \|\mathbf{L}\mathbf{m} - \mathbf{d}\|_2 \leq \sigma$$

match the data where sampled

$$\|\mathbf{W}_{\mathbf{m}}\mathbf{m}\|_2 = \|\mathbf{m}\|_1$$

Alternative method for l1 inversion using l2

L contains any kind of mapping (regular or irregular)
The sampling operator is built in the design of the transform.

Sparse transforms formulation as used in interpolation

$$\mathbf{d} = \mathbf{TLm}$$

Transformation and sampling operator

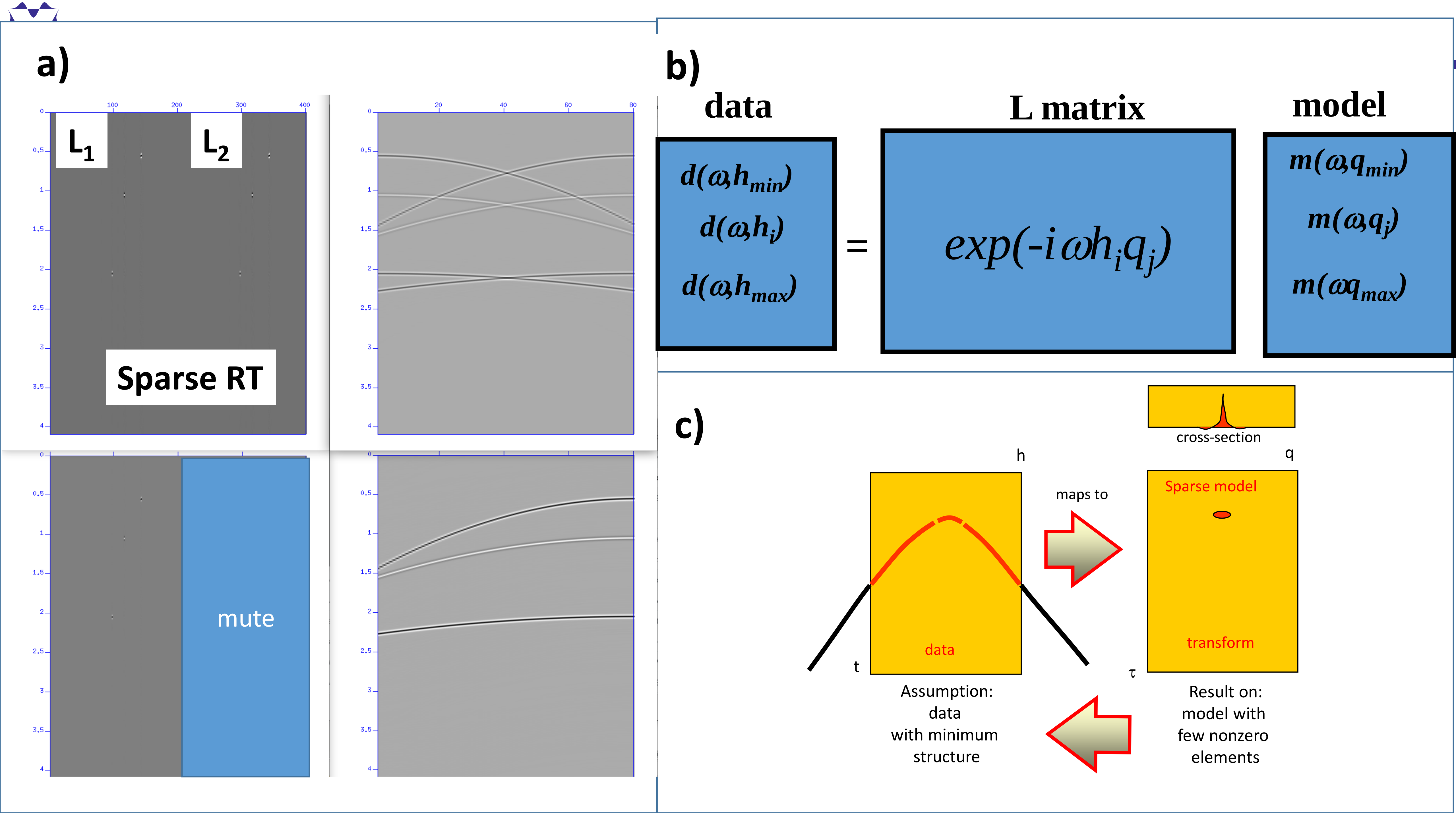
$$\text{minimize } \|\mathbf{W_m L^H x}\|_2$$

enforce sparseness in the transform coefficients

$$\text{subject to } \|\mathbf{Tx} - \mathbf{d}\|_2 \leq \sigma$$

match the data where sampled

$\mathbf{L} = \mathbf{\Psi},$	Synthesis or modeling
$\mathbf{T} = \mathbf{\Phi},$	Sampling, regular or irregular
$\mathbf{m} = \alpha,$	Model, sparse coefficients obtained through sparse inversion
$\mathbf{d} = \mathbf{y}$	Data, sampled version of **x** or **Lm**


a)
L1
L2
Sparse RT
mute
b)
data
L matrix
model
d(ω,h_min)
d(ω,h_i)
d(ω,h_max)
=
exp(-iωh_iq_j)
m(ω,q_min)
m(ω,q_j)
m(ω,q_max)
c)
cross-section
h
q
maps to
Sparse model
data
transform
t
τ
Assumption:
data
with minimum
structure
Result on:
model with
few nonzero
elements