MSc, Thesis Defence

Seismic Data Processing with the Parallel Windowed Curvelet Transform

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Outline

- Introduction
  - Motivations and goals
  - The curvelet transform
- Seismic Data processing in the curvelet domain
  - Incoherent noise removal
  - Primary multiple-separation
- Parallel windowed seismic data processing
- Parallel Seismic data processing with the parallel windowed curvelet domain
- conclusion

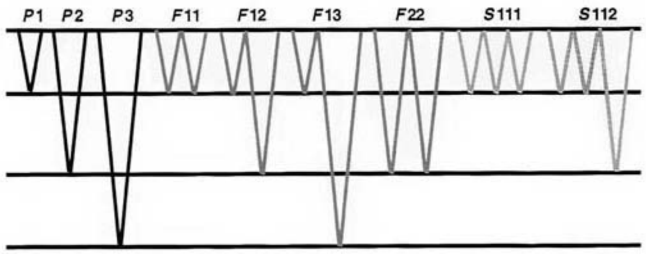
INTRODUCTION

Introduction

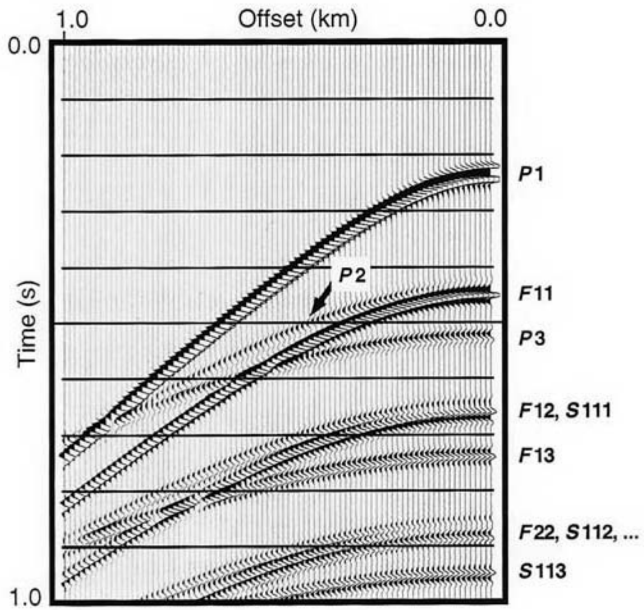
- Today, exploration of new regions with high subsurface complexities.
- Field data contains noise and possibly is incomplete.
- For complex structures, small amount of coherent noise can result in gaining or losing millions of dollars.

Synthetic example (primaries, multiples)

Wave paths



Seismic data



Adapted from Ikelle and Amundsen, 2005

Objectives

- Allow a memory demanding iterative multiple elimination method to fit in memory by dividing data into windows and distributing to processing nodes.
- Compare two ways to distribute and process windowed data:
  - Windows do not communicate edge information.
  - Windows communicate edge information.

Advantages/Disadvantages

Scenario	Advantages	Disadvantages
A	-Speed - Ease of implementation	- Reduced accuracy
B	- Accuracy	-Complex implementation -Slow runtime

Sparsity-promoting seismic data processing

- Exploit sparsifying domains to concentrate energy in few significant coefficients.
- Ex. Wavelets, Surfacelets, Curvelets, … Etc.
- Produce excellent performance for seismic problems solved with iterative thresholding methods, with relatively small number of iterations.

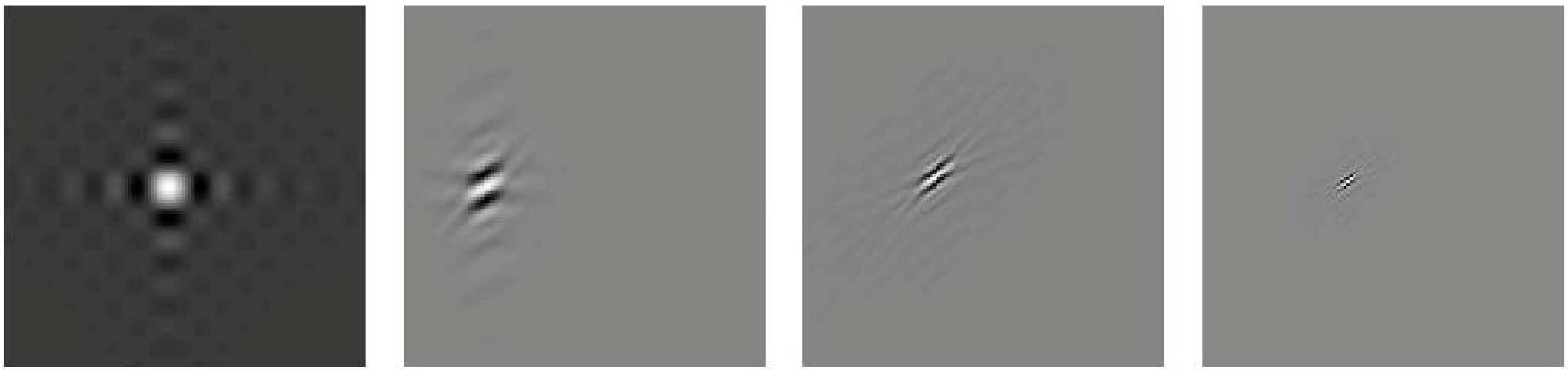
The curvelet transform

- Curvelets are **localized**, **multi-scale and multi-directional** plane-waves.

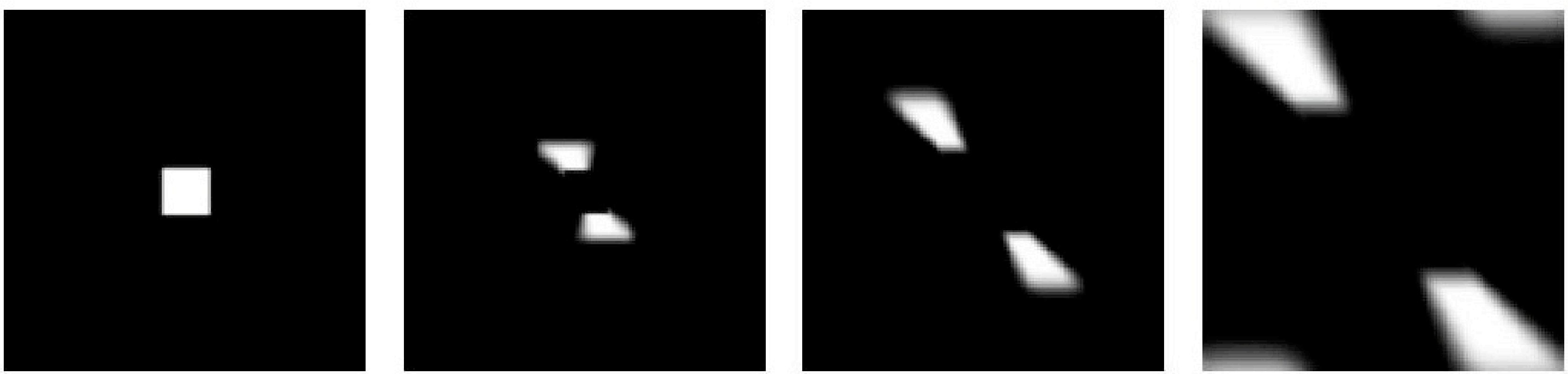
- Curvelets have an anisotropic shape. Necessary to detect wave fronts.

- Without prior information, they find the location and direction of a wave front. (principle of alignment)

The curvelet transform

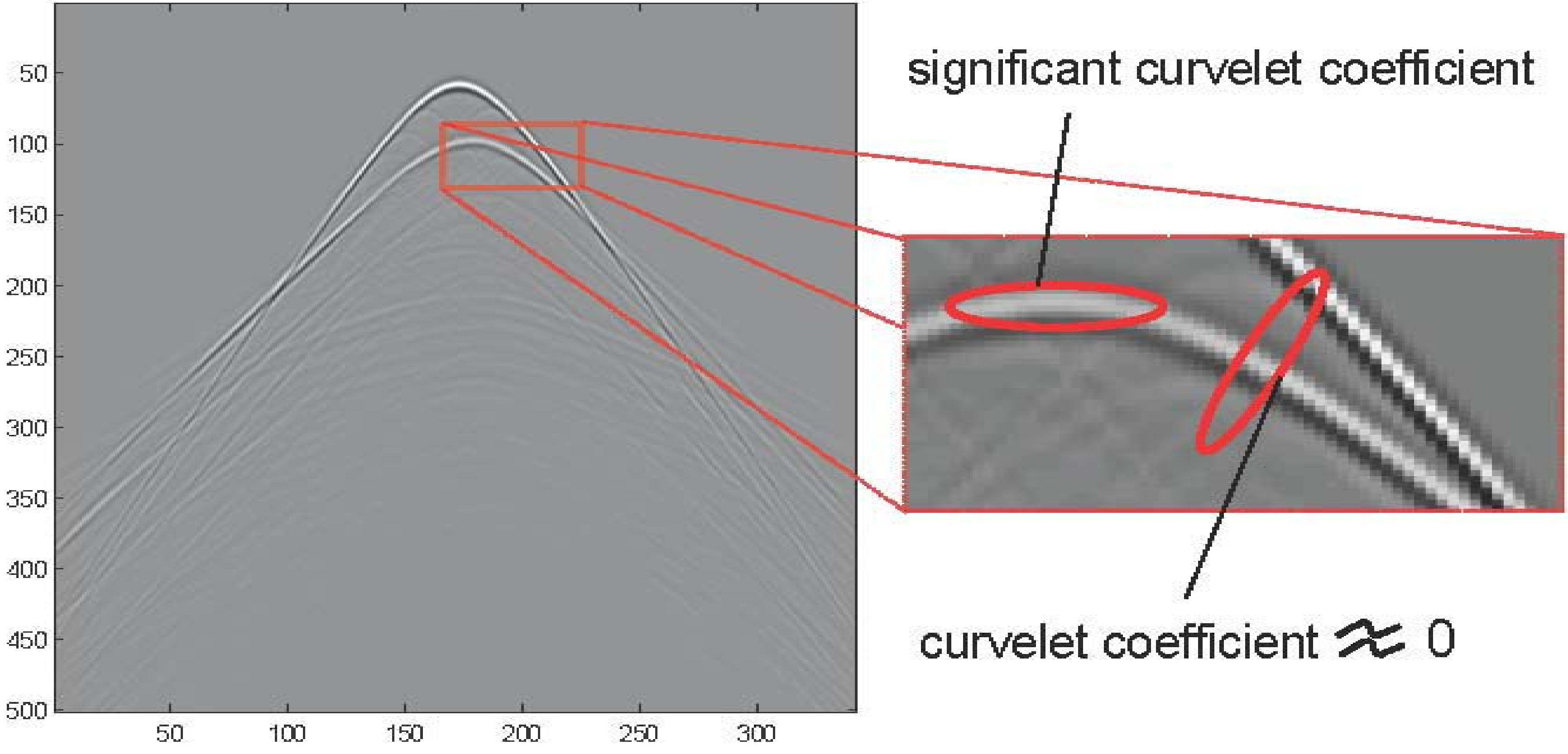


Spatial



Frequency

The curvelet transform

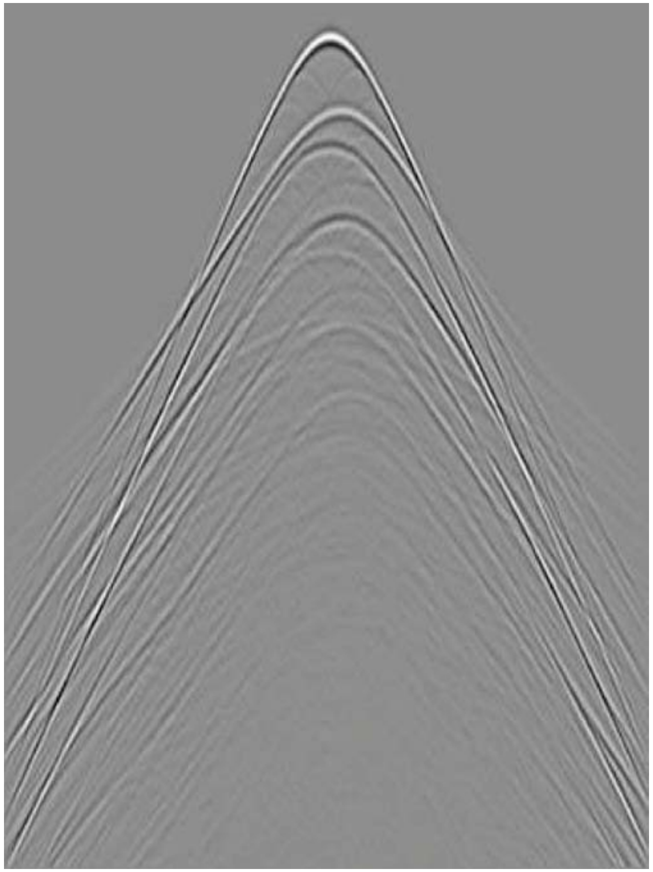


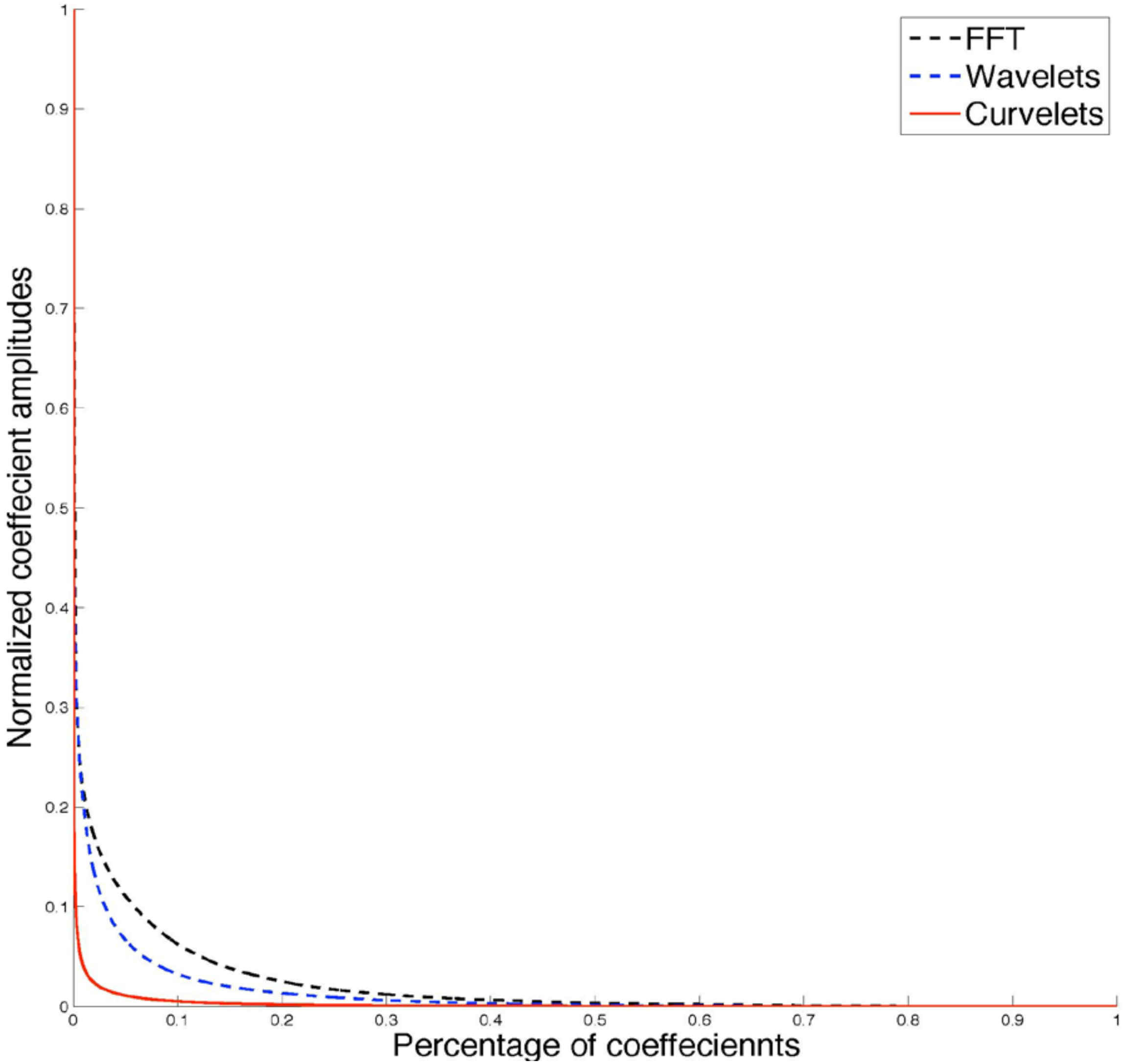
Adapted from Herrmann and Hennenfent, 2008.

The curvelet transform

- High compression rate.
- Coefficients decay faster than other transforms, ex. FFT, Wavelets.
- Computational complexity O($M \log M$)
- Redundant (8X for 2D - 24X for 3D)

The curvelet transform





Curvelet based seismic data processing

Curvelet based seismic data processing

- Incoherent noise elimination
- Coherent noise elimination; surface related multiples elimination

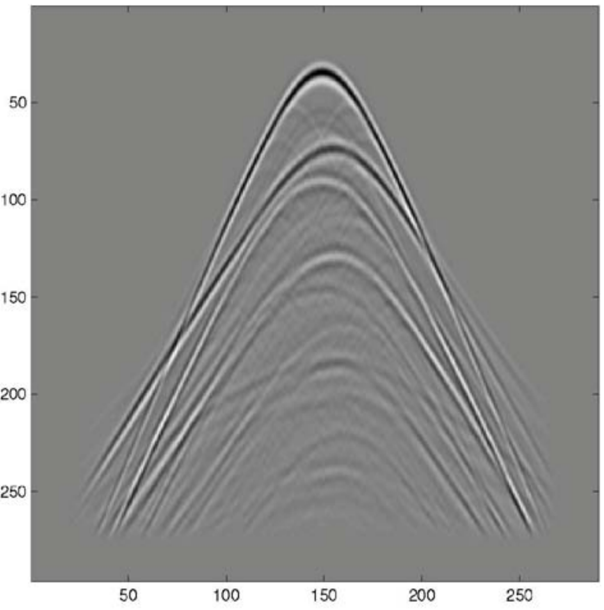
Incoherent noise removal

Incoherent noise removal problem can be cast as the optimization problem:

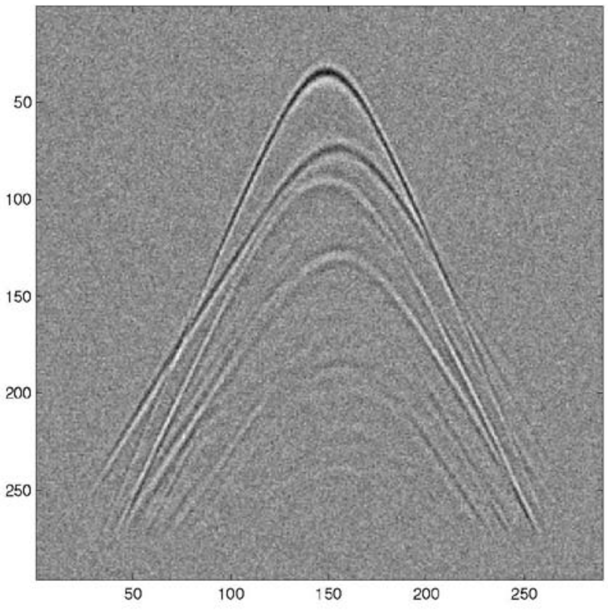
$$\min \|\mathbf{x}\|_1 \quad \text{subject to} \quad \|\mathbf{A}\mathbf{x} - \mathbf{b}\|_2 \leq \alpha$$

A: Sparsifying operator, we choose curvelets
b: Data with white Gaussian noise
x: The output denoised data
α: An estimate of the noise level in the data

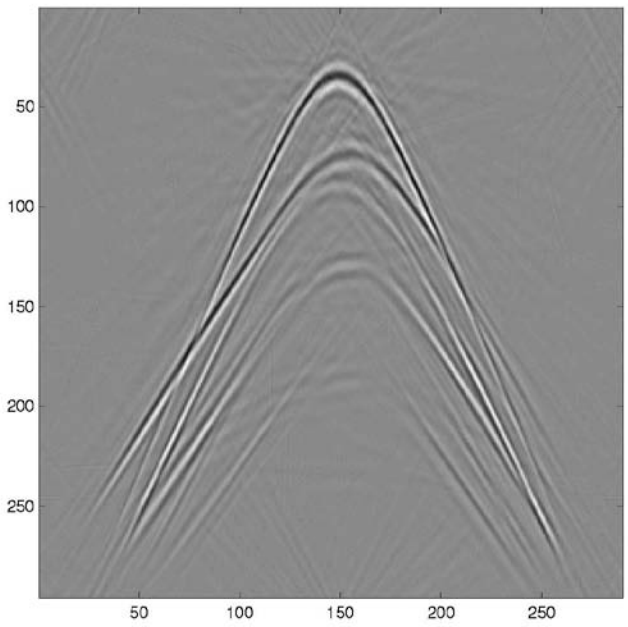
Synthetic data (SPGL1)



Noise Free



Noisy (White Gaussian sigma=1.4)



Denoised

SPGL1, van den Berg, E. and M. P. Friedlander

Coherent noise removal (surface related multiple elimination)

- Predictive methods, two steps:
  - prediction: multiples predicted from seismic data
  - separation: predicted multiples and primary reflections are separated.

Bayesian primary-multiple separation (Wang et al., 2008)

$$\mathbf{b} = \mathbf{s}_1 + \mathbf{s}_2 + \mathbf{n}$$

$$\begin{aligned}\mathbf{b}_2 &= \mathbf{s}_2 + \mathbf{n}_2 \\ \mathbf{b}_1 &= \mathbf{b} - \mathbf{b}_2 \\ &= \mathbf{s}_1 + \mathbf{n} - \mathbf{n}_2 \\ &= \mathbf{s}_1 + \mathbf{n}_1\end{aligned}$$

$$\begin{aligned}\mathbf{b}_1 &= \mathbf{A}\mathbf{x}_1 + \mathbf{n}_1 \\ \mathbf{b}_2 &= \mathbf{A}\mathbf{x}_2 + \mathbf{n}_2\end{aligned}$$

Maximize:

$$P(\mathrm{x}_1, \mathrm{x}_2 | \mathrm{b}_1, \mathrm{b}_2) = P(\mathrm{x}_1, \mathrm{x}_2) P(\mathrm{n}) P(\mathrm{n}_2) / P(\mathrm{b}_1, \mathrm{b}_2)$$

Bayesian primary-multiple separation (Wang et al., 2008)

$$\min_{\mathbf{x}_1, \mathbf{x}_2} \quad f(\mathbf{x}_1, \mathbf{x}_2)$$

$$f(\mathbf{x}_1, \mathbf{x}_2) =$$

$$\lambda_1 \|\mathbf{x}_1\|_{1,\mathrm{w}_1} + \lambda_2 \|\mathbf{x}_2\|_{1,\mathrm{w}_2} + \|\mathbf{A}\mathbf{x}_2 - \mathbf{b}_2\|_2^2 \; + \eta \|\mathbf{A}(\mathbf{x}_1 + \mathbf{x}_2) - \mathbf{b}\|_2^2$$

$$\mathbf{w}_1 = \max\{|\mathbf{A}^{\mathrm{T}}\mathrm{b}_2|, \epsilon\}$$
$$\mathbf{w}_2 = \max\{|\mathbf{A}^{\mathrm{T}}\mathrm{b}_1|, \epsilon\}$$

Algorithm: Bayesian iterative method for wavefield separation

input: $\mathbf{b}_1$,$\mathbf{b}_2$,λ_1, λ_2, η, niter
$\tilde{\mathbf{x}}_1 = 0$,$\tilde{\mathbf{x}}_2 = 0$

threshold $\mathbf{w}_1 = \frac{\lambda_1 |\mathbf{A}^T \mathbf{b}_2|}{2\eta}$
threshold $\mathbf{w}_2 = \frac{\lambda_2 |\mathbf{A}^T \mathbf{b}_1|}{2(\eta+1)}$

$\hat{\mathbf{b}_1} = \mathbf{A}^T \mathbf{b}_1$
$\hat{\mathbf{b}_2} = \mathbf{A}^T \mathbf{b}_2$

for i = 1 : niter

$$\mathbf{x}_1 = \hat{\mathbf{b}_2} - \mathbf{A}^T \mathbf{A} \tilde{\mathbf{x}}_2^n + \hat{\mathbf{b}_1} - \mathbf{A}^T \mathbf{A} \tilde{\mathbf{x}}_1^n + \tilde{\mathbf{x}}_1^n$$
$$\mathbf{x}_2 = \hat{\mathbf{b}_2} - \mathbf{A}^T \mathbf{A} \tilde{\mathbf{x}}_2^n + \frac{\eta}{\eta+1} \left(\hat{\mathbf{b}_1} - \mathbf{A}^T \mathbf{A} \tilde{\mathbf{x}}_1^n \right)$$

$$\tilde{\mathbf{x}}_\mathbf{1} = \frac{x_1}{|x_1|} \cdot \max(0, |\mathbf{x}_1| - |\mathbf{w}_1|)$$
$$\tilde{\mathbf{x}}_\mathbf{2} = \frac{x_2}{|x_2|} \cdot \max(0, |\mathbf{x}_2| - |\mathbf{w}_2|)$$

end

$\tilde{\mathbf{s}}_1 = \mathbf{A}\tilde{\mathbf{x}}_1$; $\tilde{\mathbf{s}}_2 = \mathbf{A}\tilde{\mathbf{x}}_2$

Based on the work of Daubechies et al., 2004

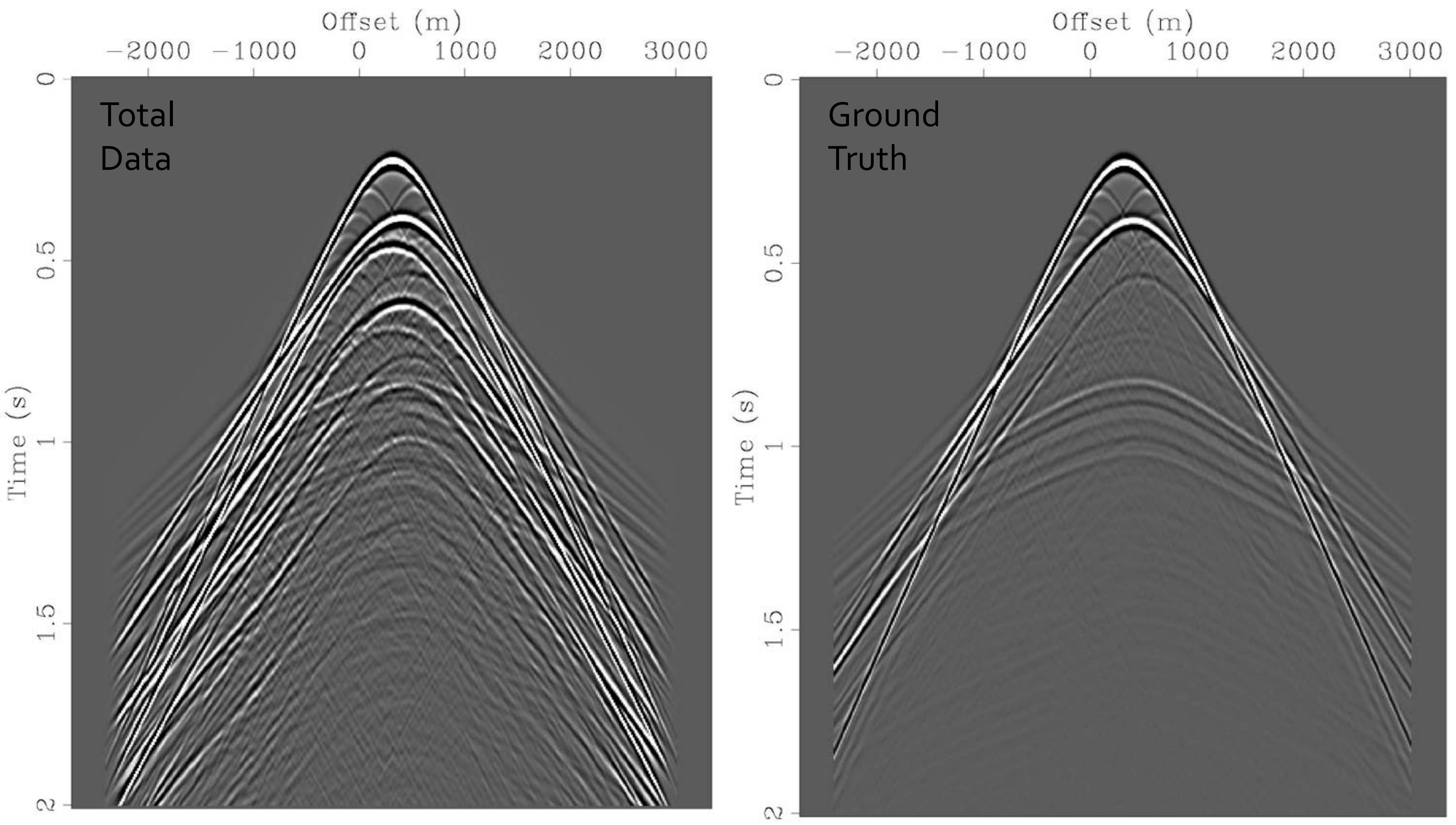
SNR

$$\{\lambda_1^* = 0.8, \lambda_2^* = 1.2, \eta^* = 1.2\}$$

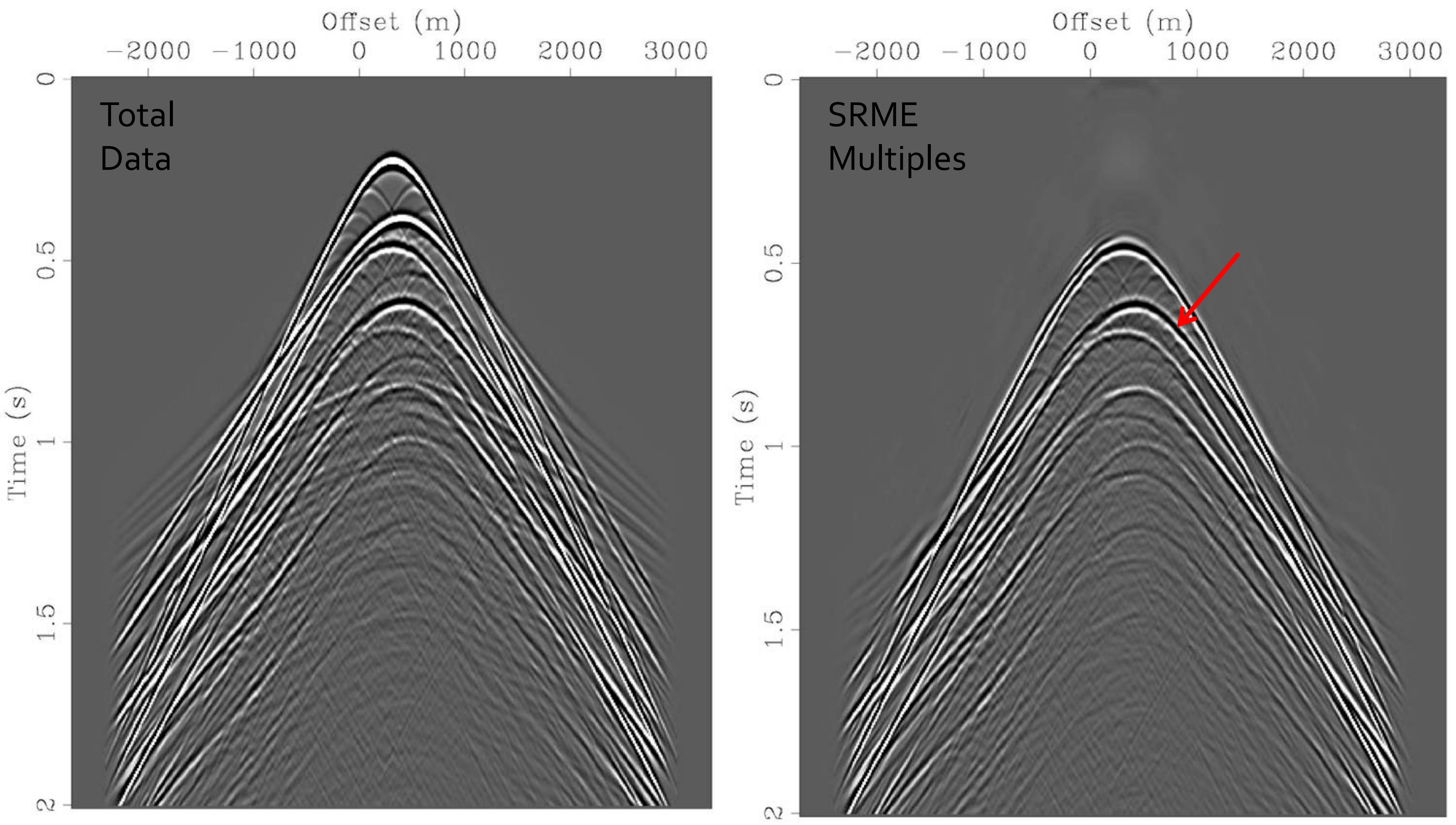
$$\mathrm{SNR} = 20\log_{10}\frac{\left\|\frac{\boldsymbol{s}_1}{\|\boldsymbol{s}_1\|_2}\right\|}{\left\|\frac{\tilde{\boldsymbol{s}}_1}{\|\tilde{\boldsymbol{s}}_1\|_2} - \frac{\boldsymbol{s}_1}{\|\boldsymbol{s}_1\|_2}\right\|_2}$$

SNR (dB)	$\{\lambda_1^*, \lambda_2^*\}$	$\{2\cdot\lambda_1^*, \lambda_2^*\}$	$\{\lambda_1^*, 2\cdot\lambda_2^*\}$	$100\cdot\{\lambda_1^*, \lambda_2^*\}$
η^*	11.49	11.11	11.40	-
$\frac{1}{2}\cdot\eta^*$	11.29	10.38	11.15	-
$2\cdot\eta^*$	10.90	11.38	10.81	-
$100\cdot\eta^*$	-	-	-	10.99

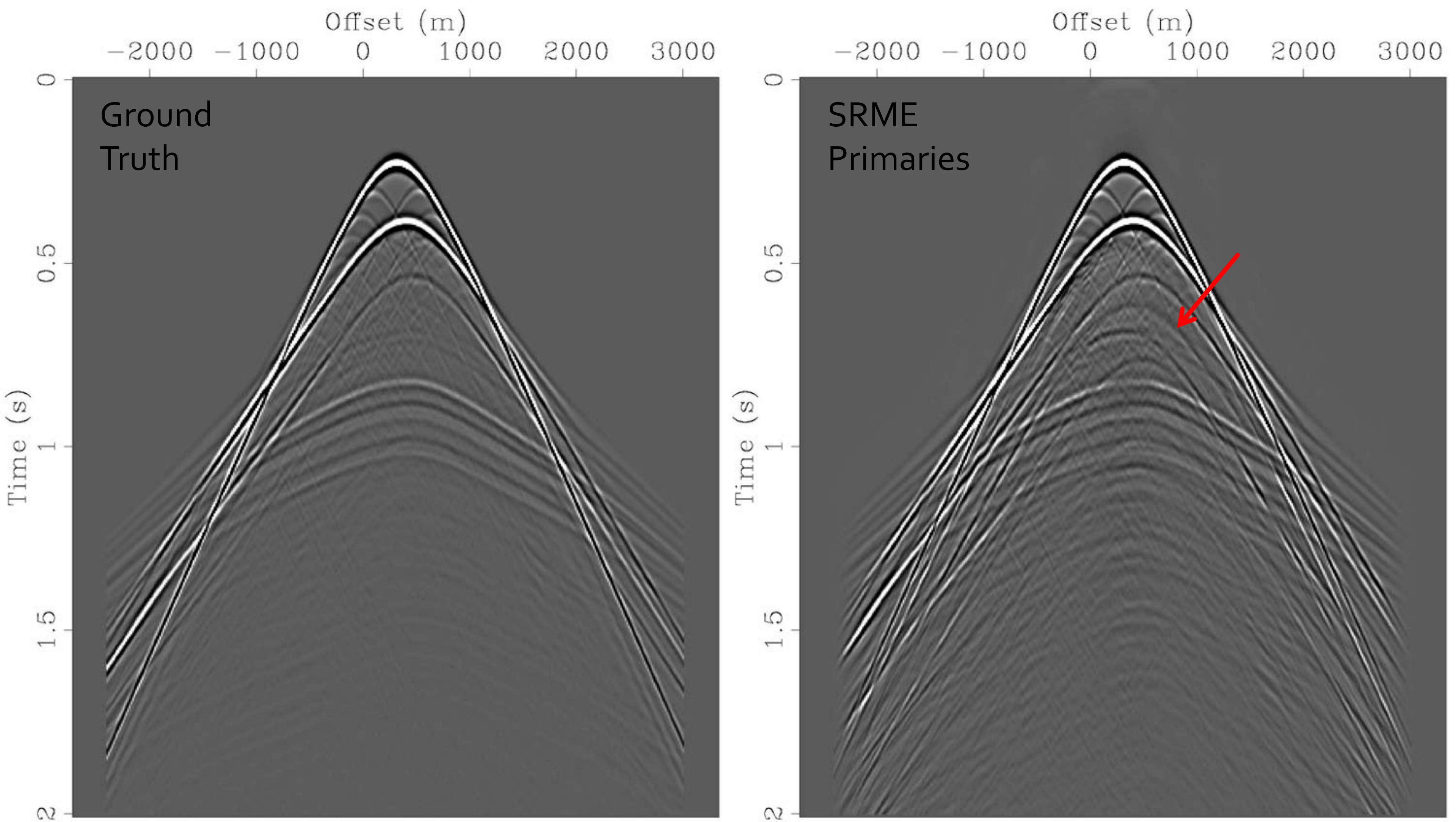
Synthetic Data



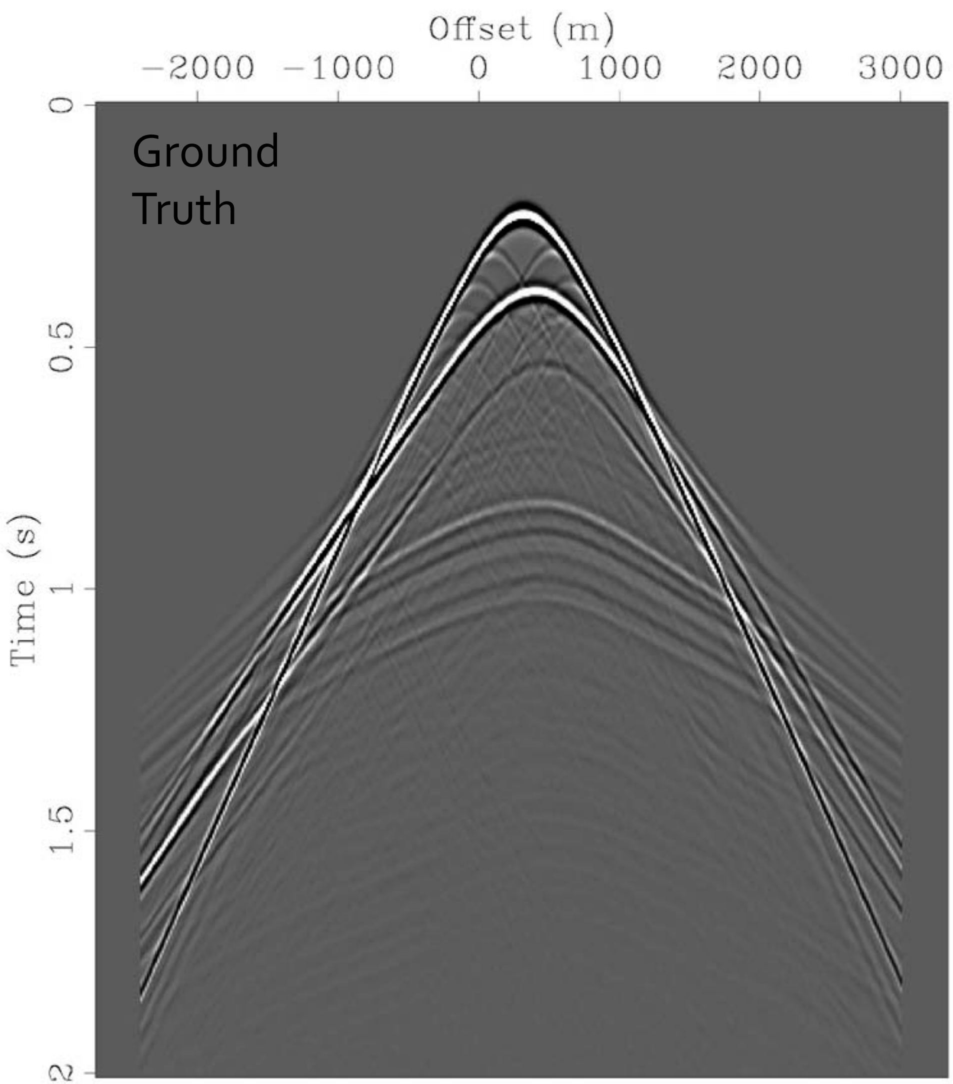
Synthetic Data

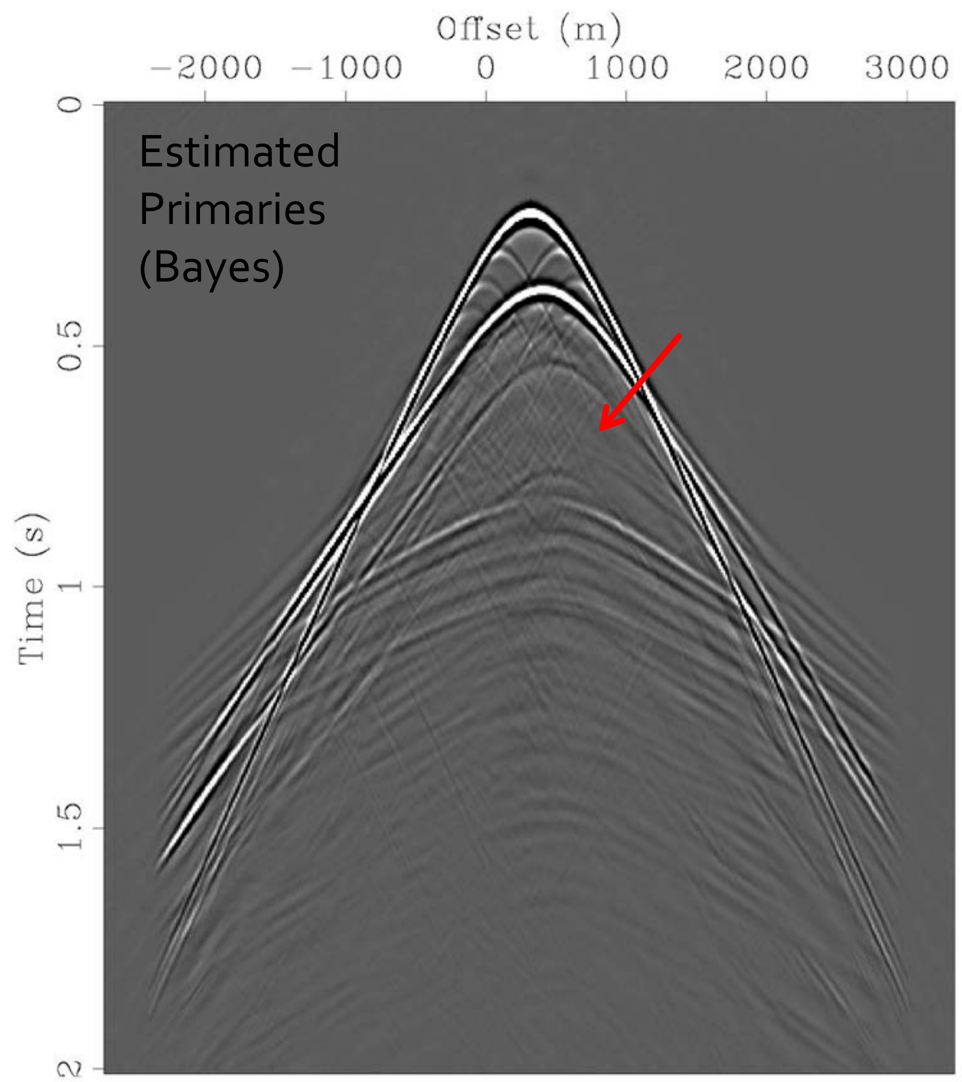


Synthetic Data



Synthetic Data





Parallel windowed seismic data processing

Parallel windowed seismic data processing

- Seismic data have large size, can reach several terabytes.
- Curvelet domain produces excellent results, but is a redundant transform (8X,24X).
- Cannot fit data in memory of a single processing unit.

Parallel windowed seismic data processing

- Possible solution:

  Define windowing operator that divides data into smaller manageable windows, each window is processed, and gathered in the end.

Parallel windowed seismic data processing

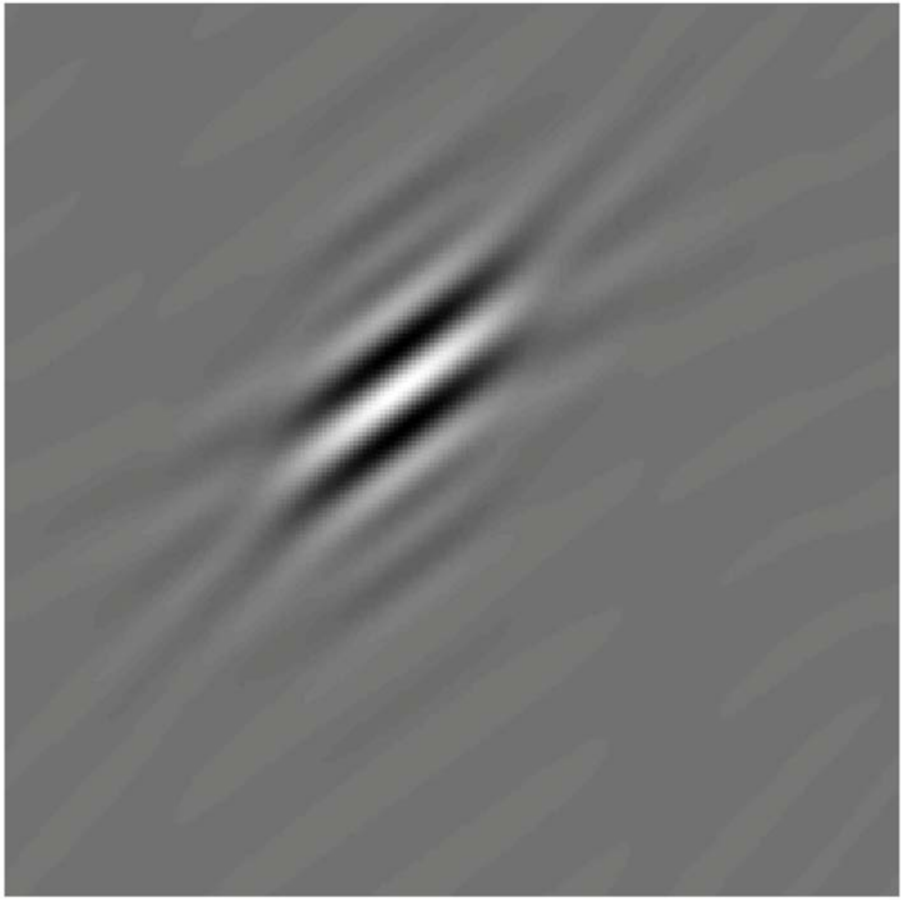
- Windowing issues:

  Artifacts, dimming and other issues at the windows borders.

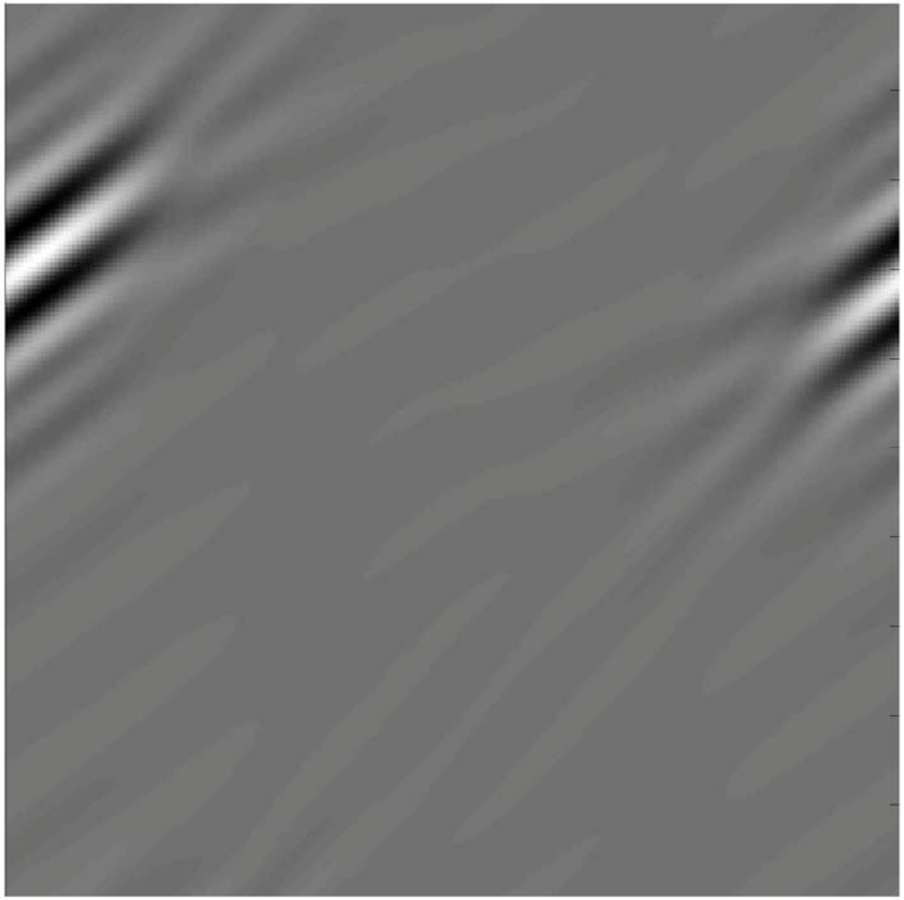
  Curvelets near borders wrap to opposite border.

  Inherit FFT problems

Parallel windowed seismic data processing



Parallel windowed seismic data processing

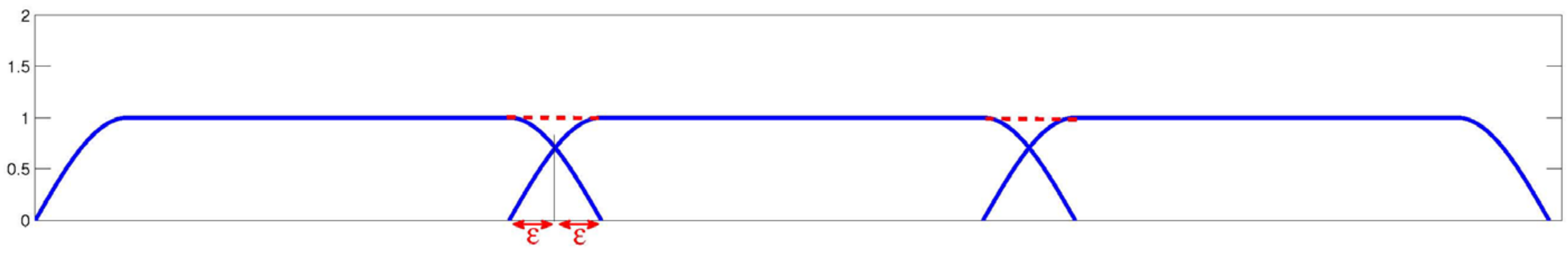


Parallel windowed seismic data processing

Solution:
Introduce overlaps and tapering

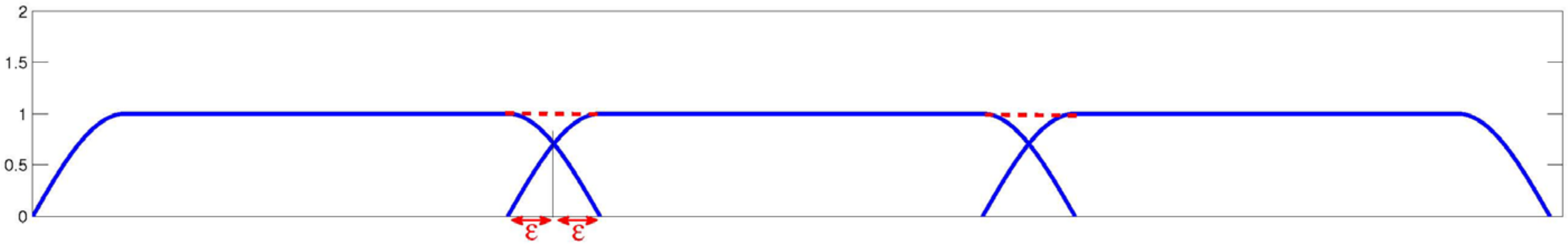
ex:

$$\mathbf{T}_n = \sin\left(\frac{(N-n)\pi}{2(2\epsilon-1)}\right), \qquad n = \{N, N-1, ..., N-2\epsilon+1\}$$



Tapering

$$\mathbf{T}_1^2 + \mathbf{T}_2^2 = 1$$



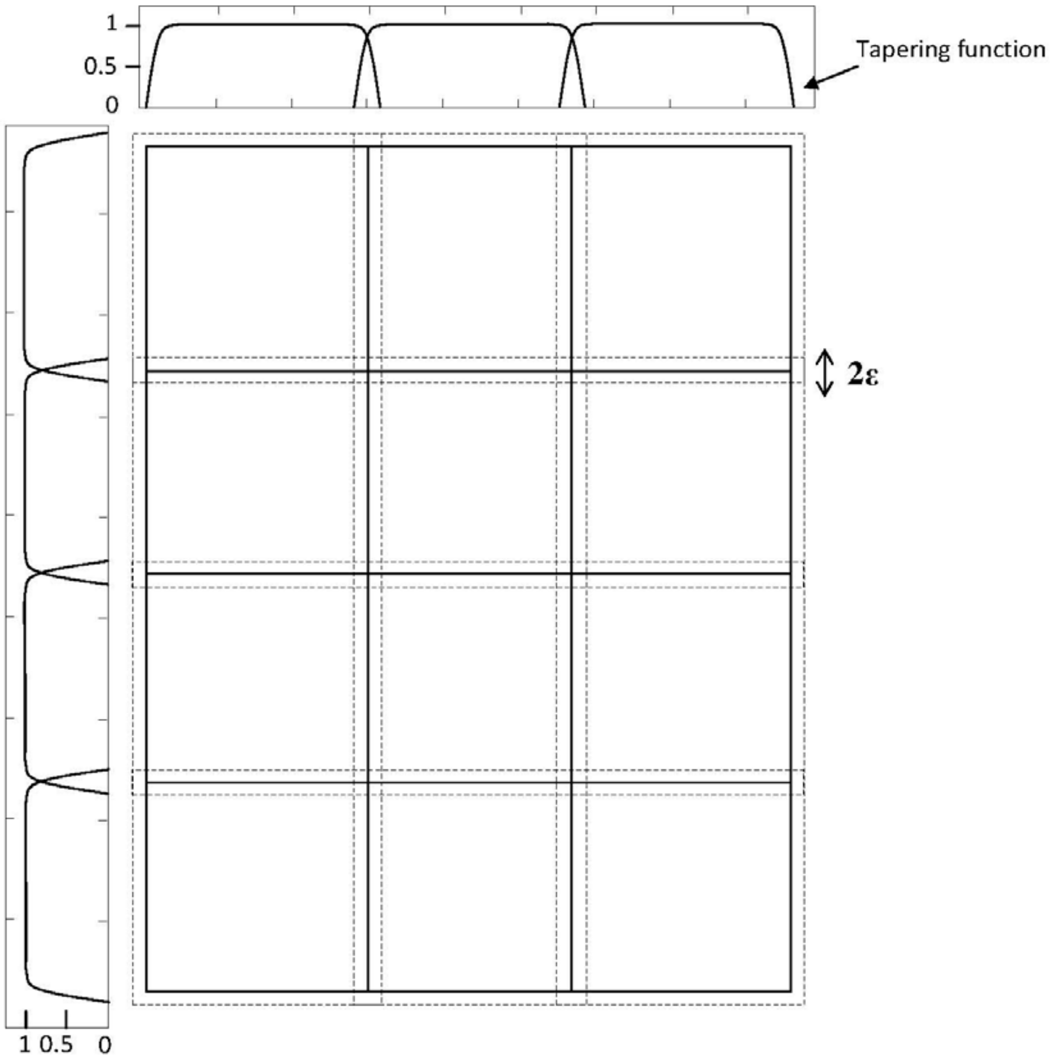
- Partition of unity
- Preserve system energy
- Smooth transition between windows

Parallel windowed seismic data processing

$$\mathbf{W}^*\mathbf{T}^*\mathbf{T}\mathbf{W} = \mathbf{I}$$

$\mathbf{W}$: Windowing operator (scattering)
$\mathbf{W}^*$: Adjoint windowing operator (gathering)
$\mathbf{T}$: Tapering operator
$\mathbf{T}^*$: Adjoint tapering operator

Parallel windowed seismic data processing



Parallel windowed seismic data processing

We can redefine our sparsifying operators in previous problems as follows:

$$\begin{aligned}\mathbf{A}^{\mathrm{T}} &= [\mathbf{C}]\mathbf{T}\mathbf{W} \\ \mathbf{A} &= \mathbf{W}^{*}\mathbf{T}^{*}[\mathbf{C}^{*}].\end{aligned}$$

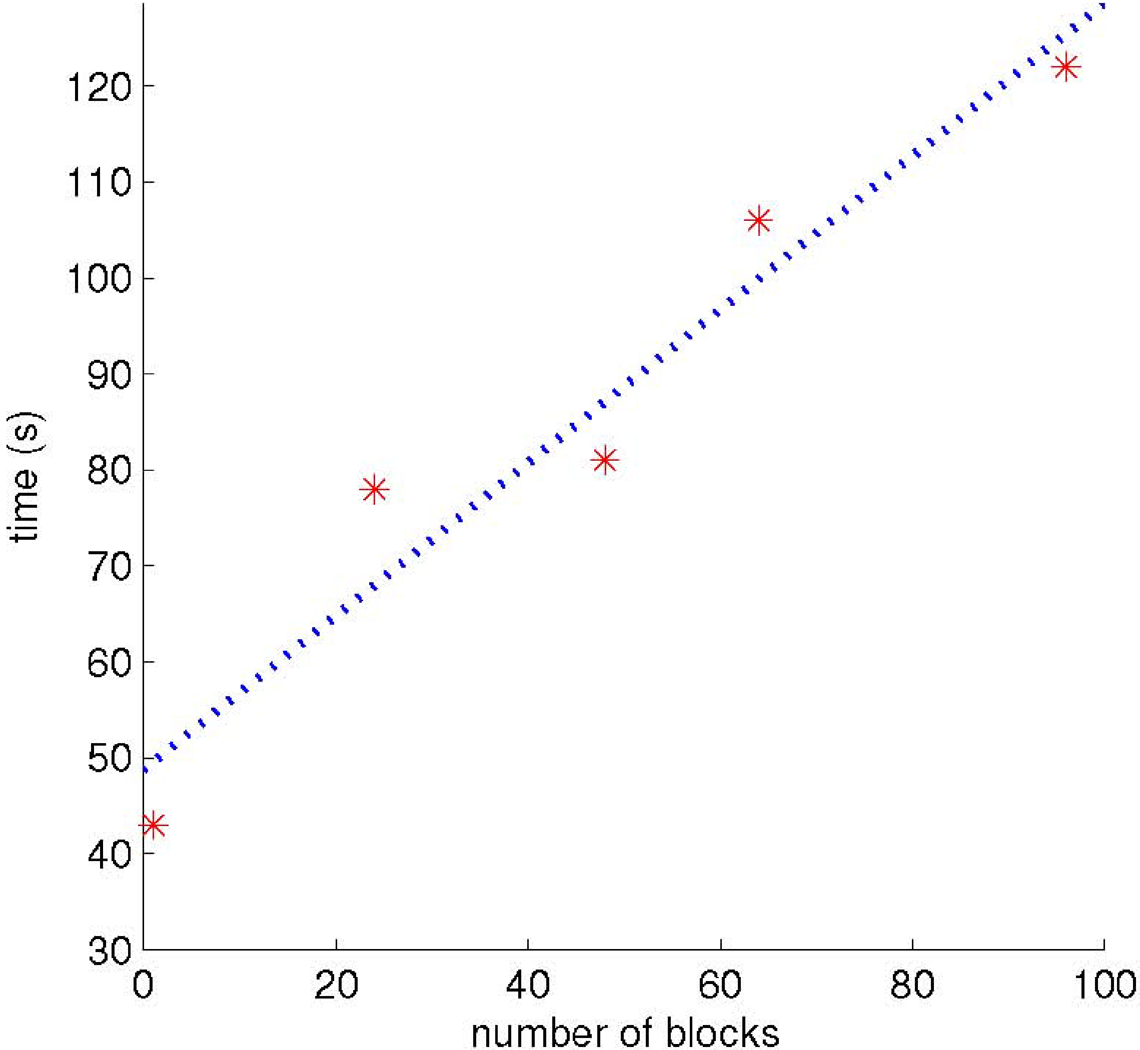
Parallel windowed seismic data processing

- Two Scenarios:
  - Scenario A:

    Window data with overlaps and tapering, then process each window independently, and at the final stage unwindow (gather data).
  - Scenario B:

    Window data with overlaps and tapering, then process each window independently, but allow windows edges to communicate, and at the final stage unwindow (gather data)

Scalability



- Single forward transform

- Block size:128X128X128

-A block of 1536X512X256:
422 seconds single block
123 seconds in parallel

Parallel windowed seismic data processing

Experiments and Results

Parallel seismic data processing with windowed curvelets

- Run previous seismic data processing problems using parallel windowed curvelet transform
- Run and compare scenarios A and B
- Start with denoising, then primary multiple separation

Denoising with the parallel curvelet transform

Scenario A

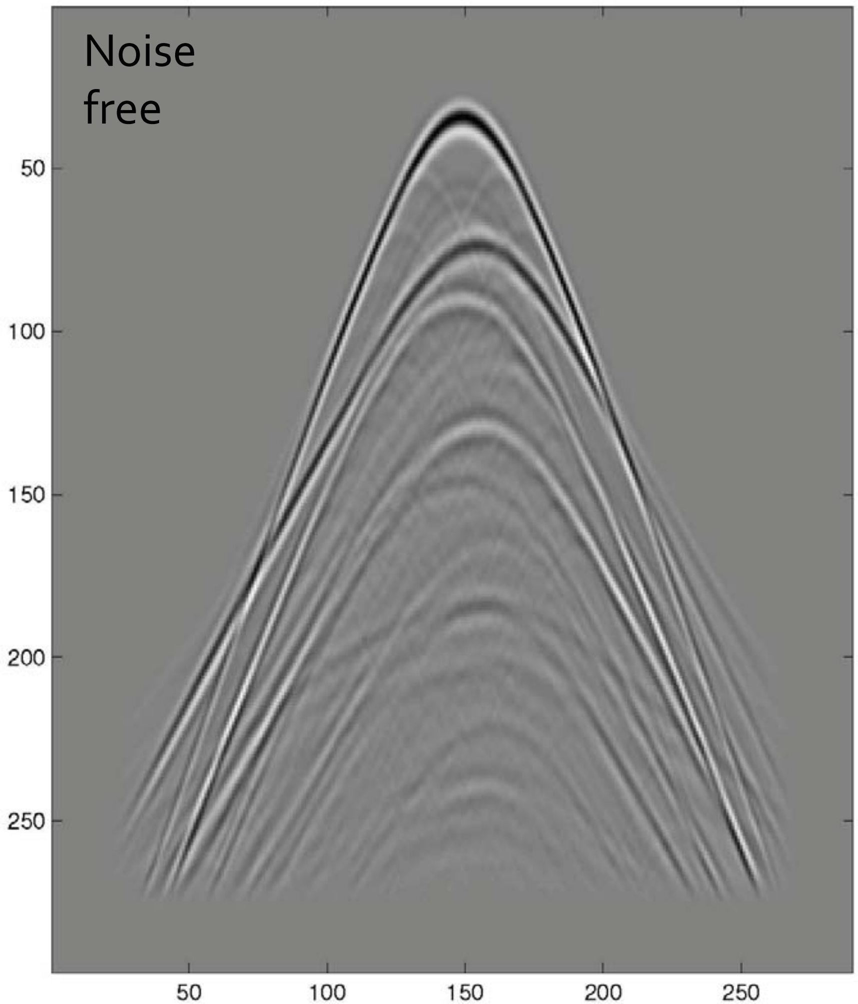
Window	SNR
1X2	6.89
2X2	6.97
1X4	8.11
4X4	7.02

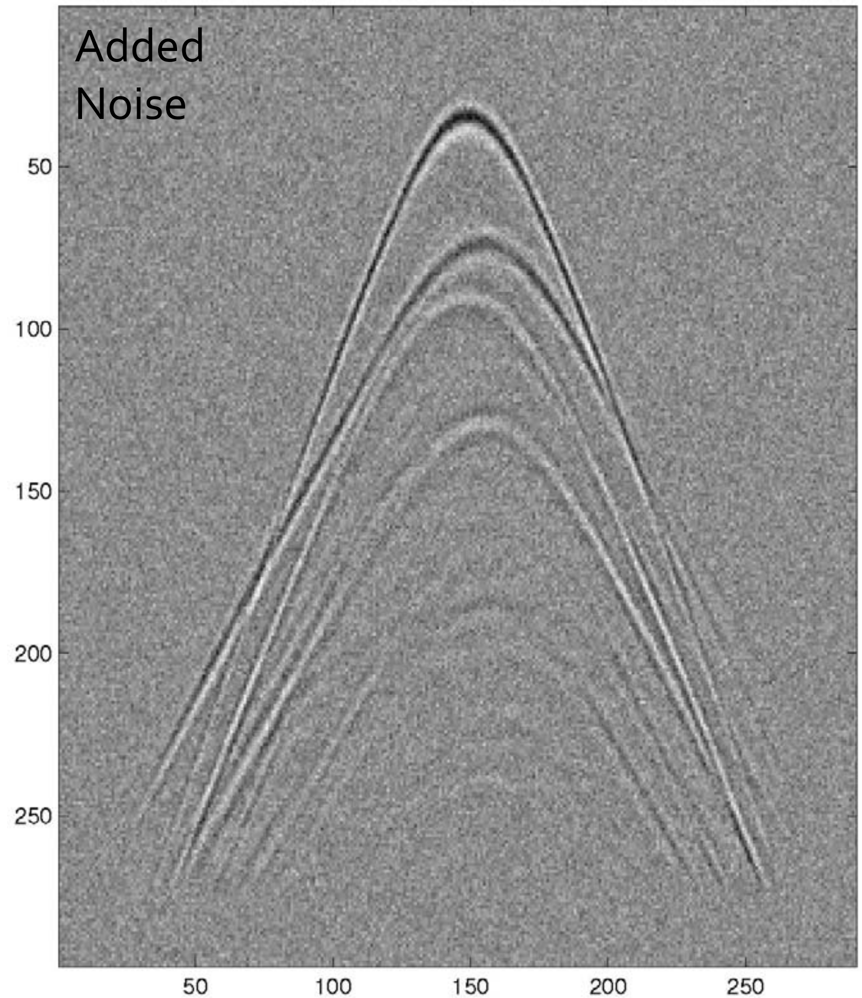
Scenario B

Window	SNR
1X2	7.26
2X2	7.38
1X4	10.34
4X4	7.50

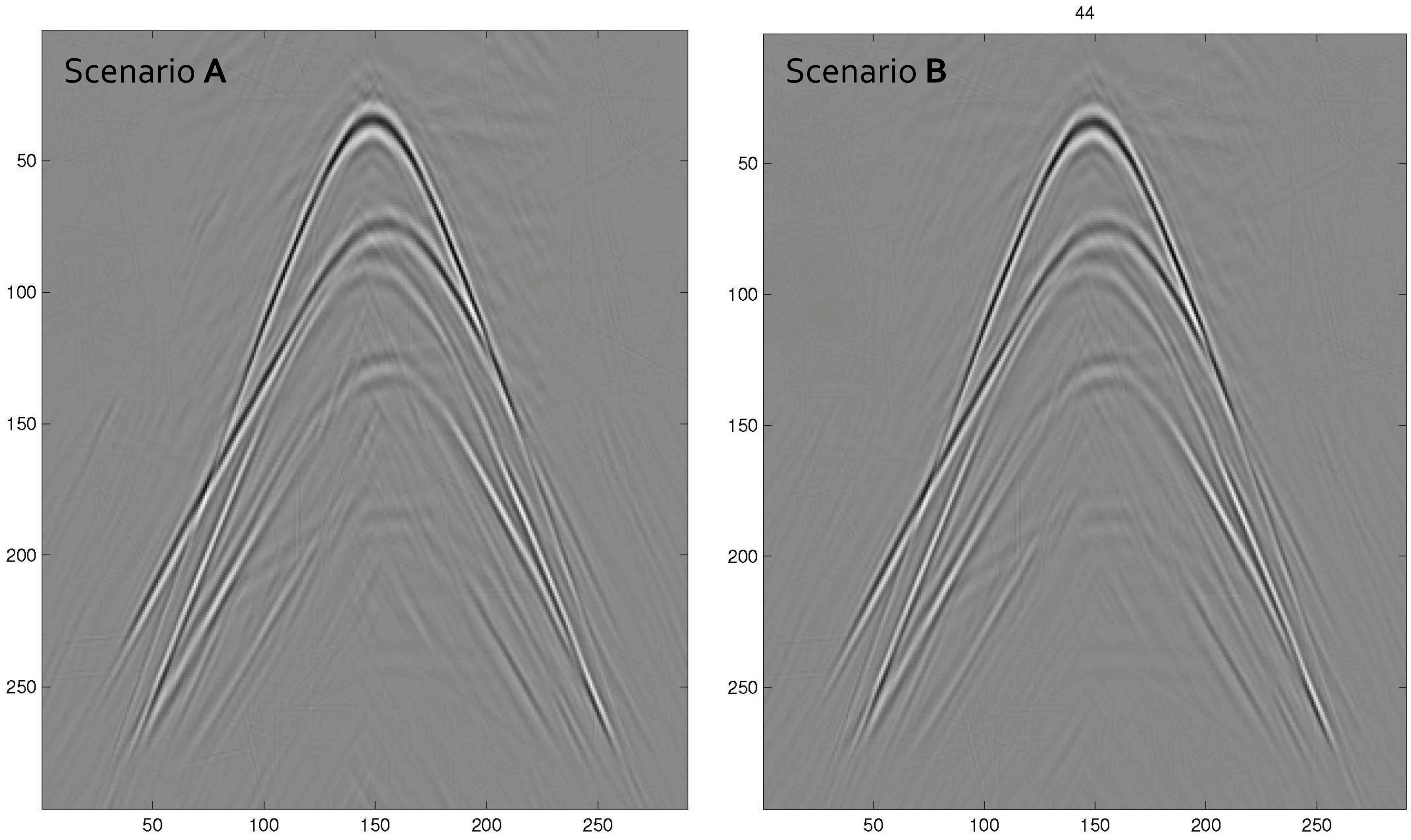
Overlap $\varepsilon=16$

Denoising with the parallel curvelet transform





Denoising with the parallel curvelet transform



Bayesian based primary-multiple separation with the parallel curvelet transform

- Synthetic Data:

361 shots

361 traces/shot

501 time samples with sample interval $\Delta t=4$ ms

- For 2D, used one shot record.

Bayesian based primary-multiple separation (2D SNR)

Scenario A

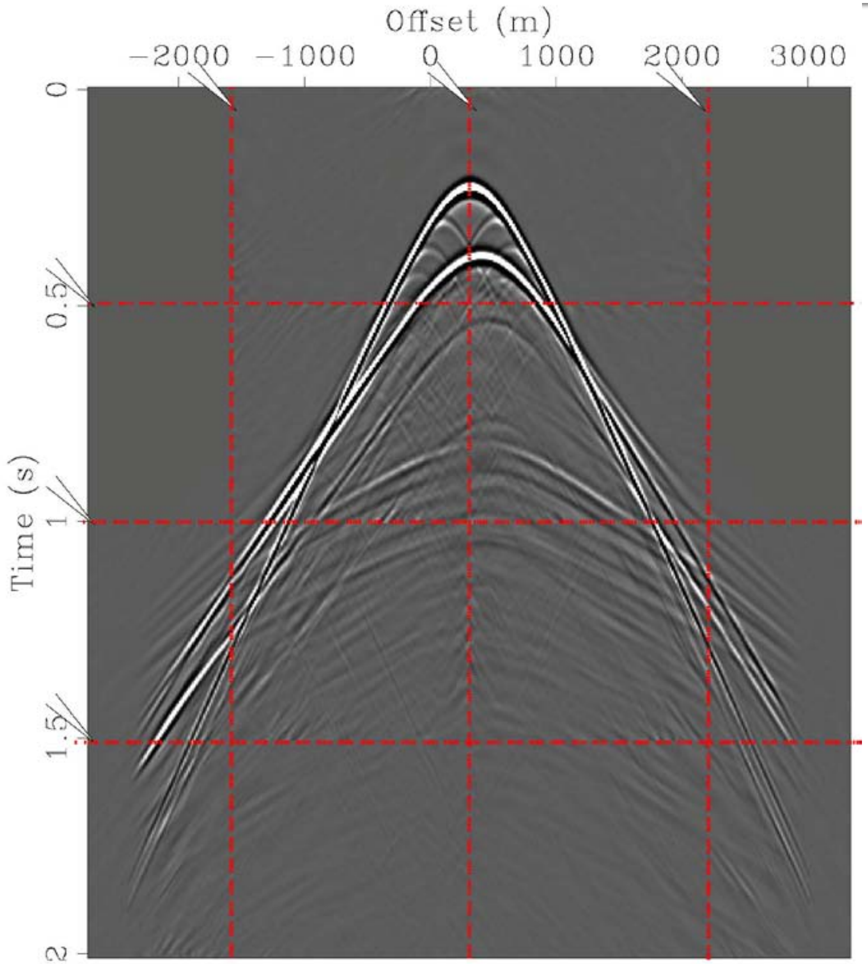
Window	SNR
2X2	11.44
2X3	11.43
1X4	11.42
4X4	11.41

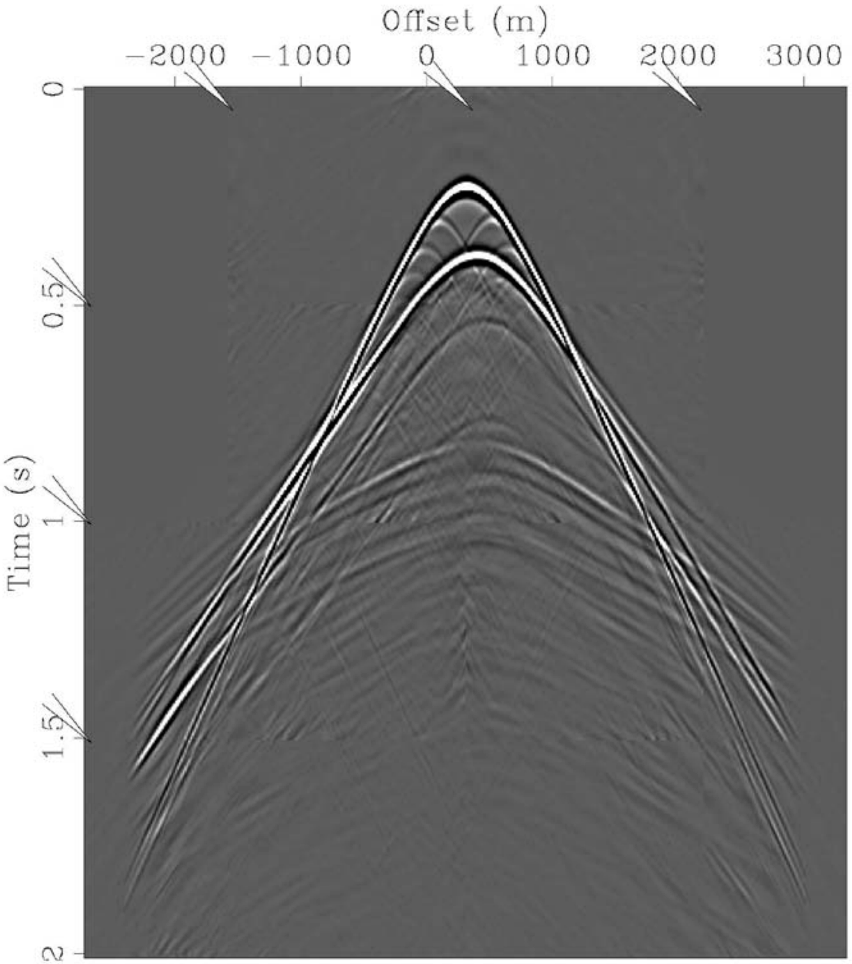
Scenario B

Window	SNR
2X2	11.46
2X3	11.46
1X4	11.43
4X4	11.43

Overlap ε=15

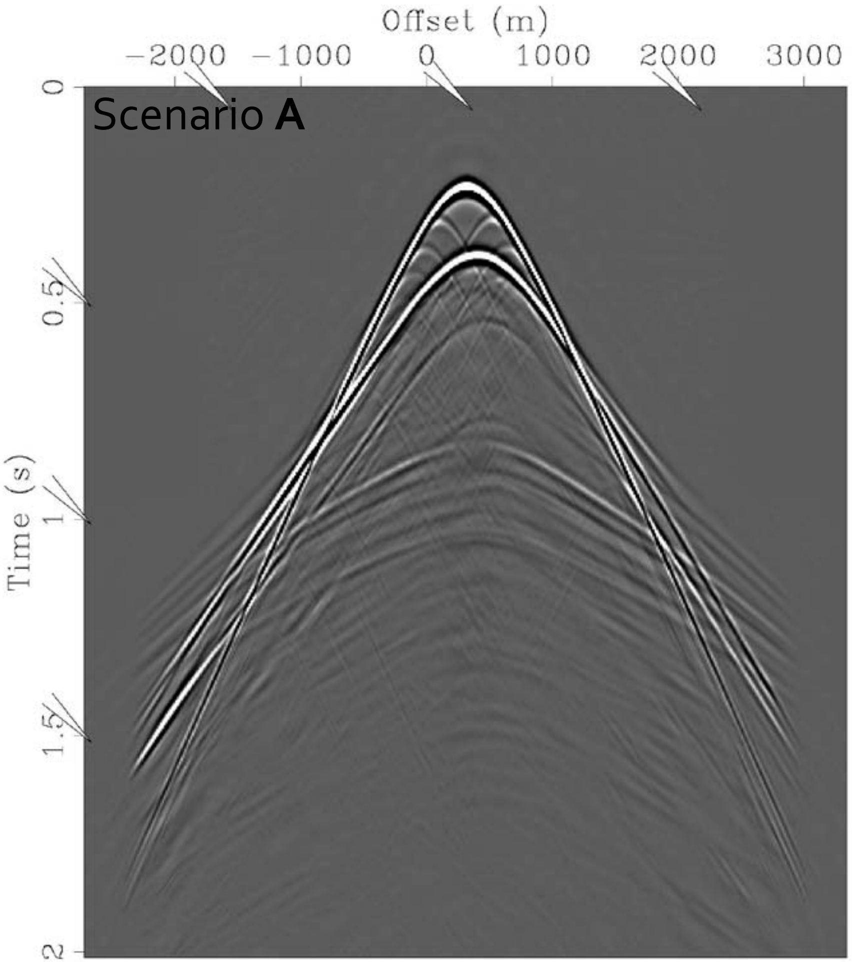
Bayesian based primary-multiple separation (2D)

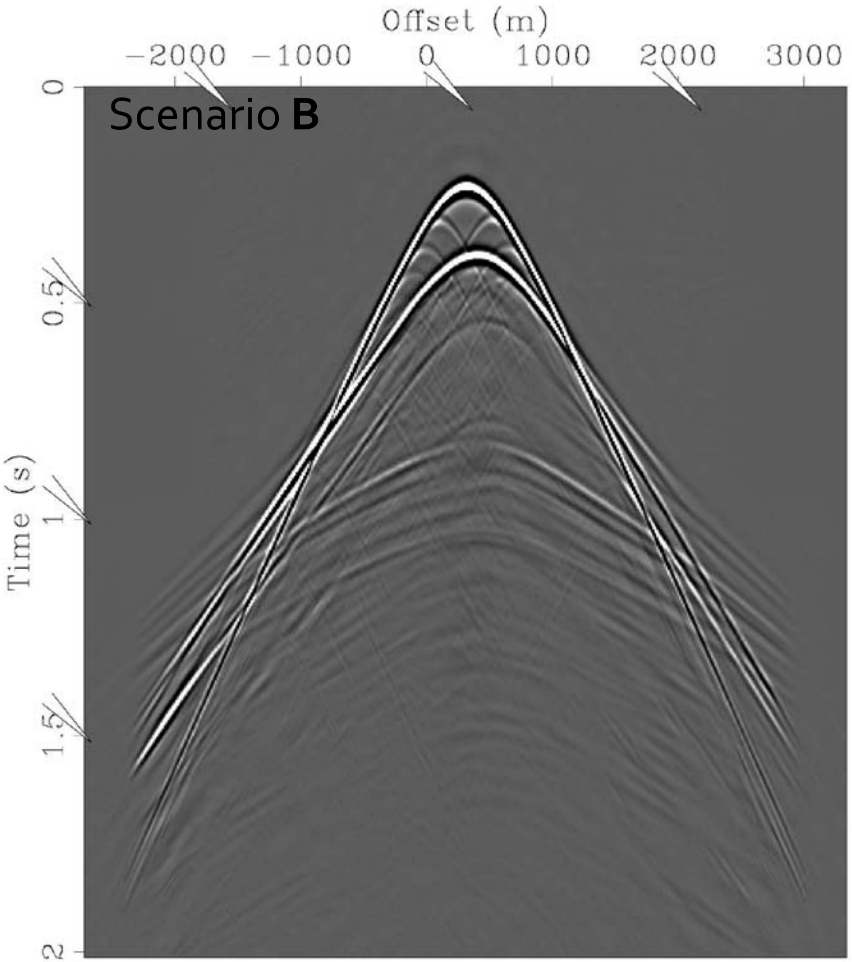




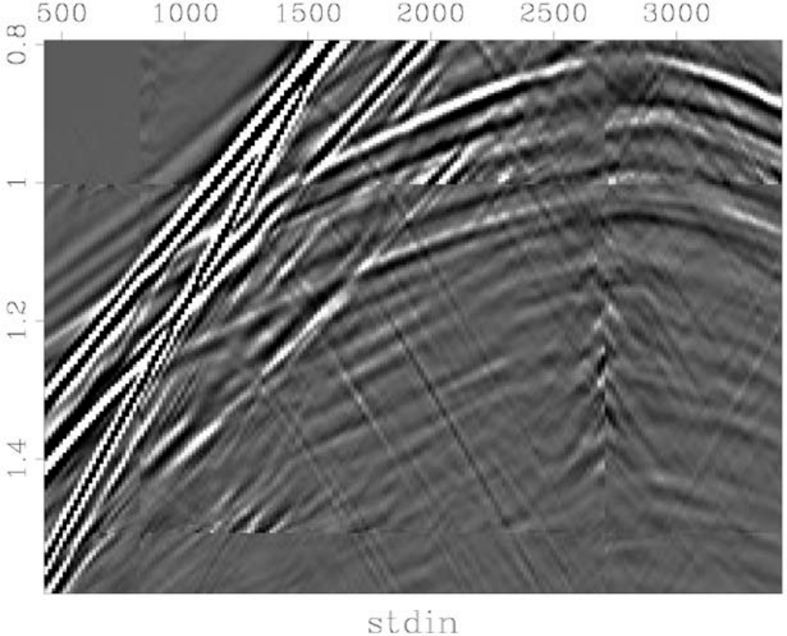
No Overlap

Bayesian based primary-multiple separation (2D)

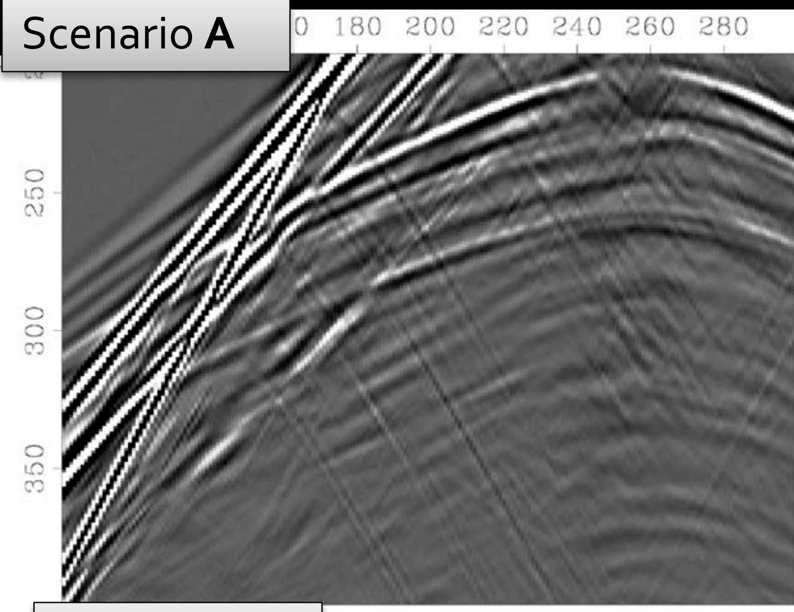




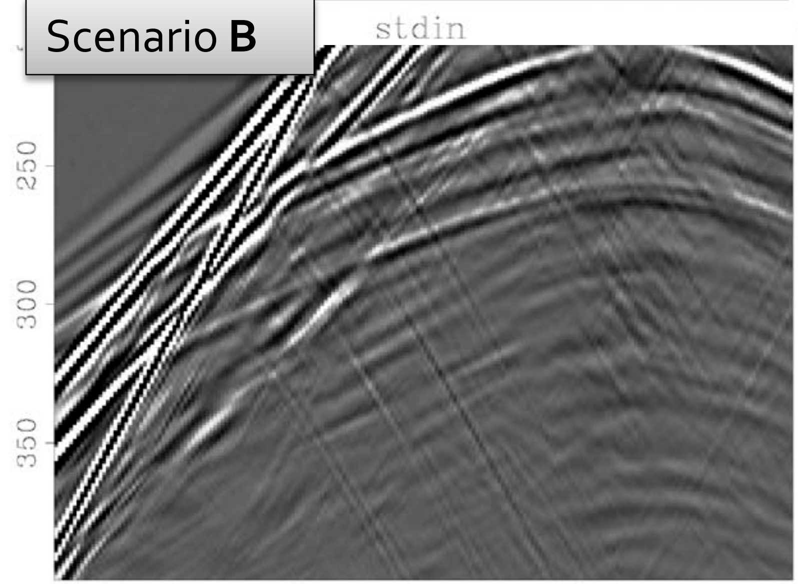
Bayesian based primary-multiple separation (2D)



Scenario **A**



Scenario **B**



Scenario **B**

Bayesian based primary-multiple separation (3D)

Scenario A

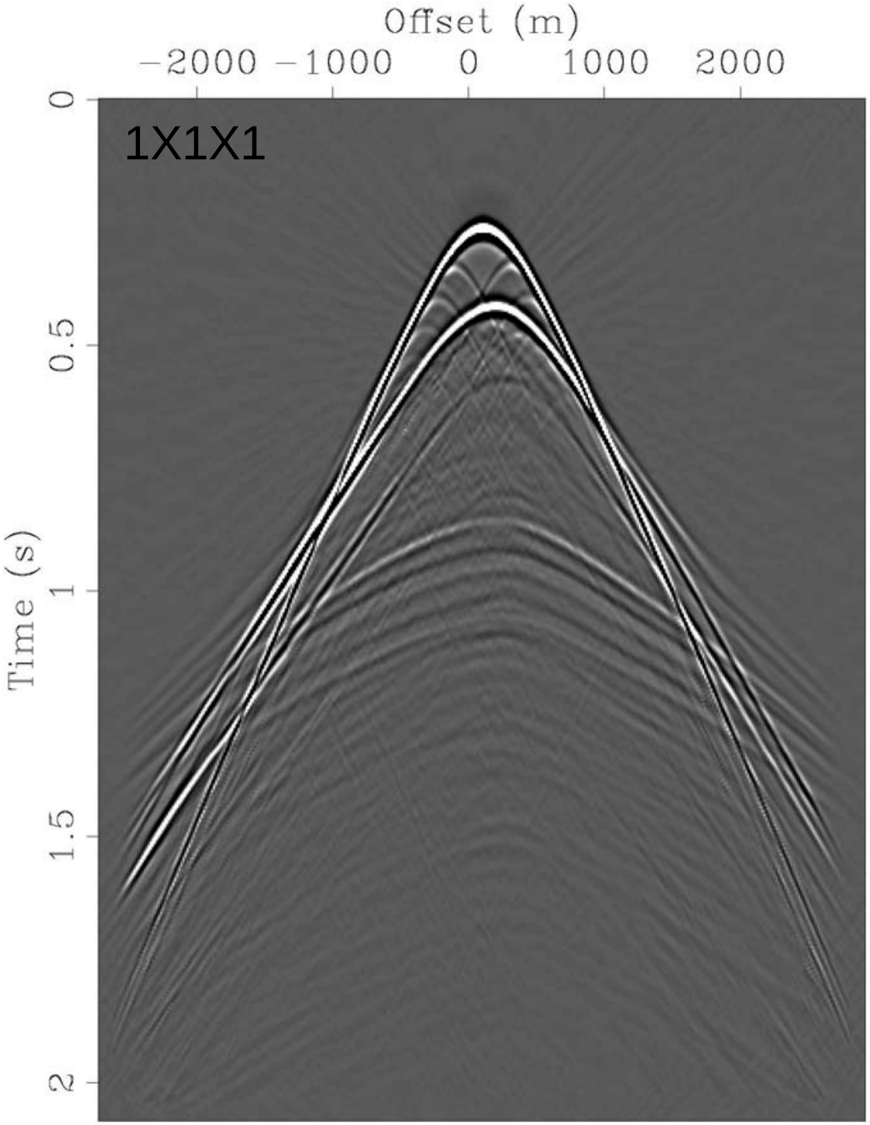
Window	SNR
2X2X2	11.50
2X4X4	11.50
4X4X2	11.46

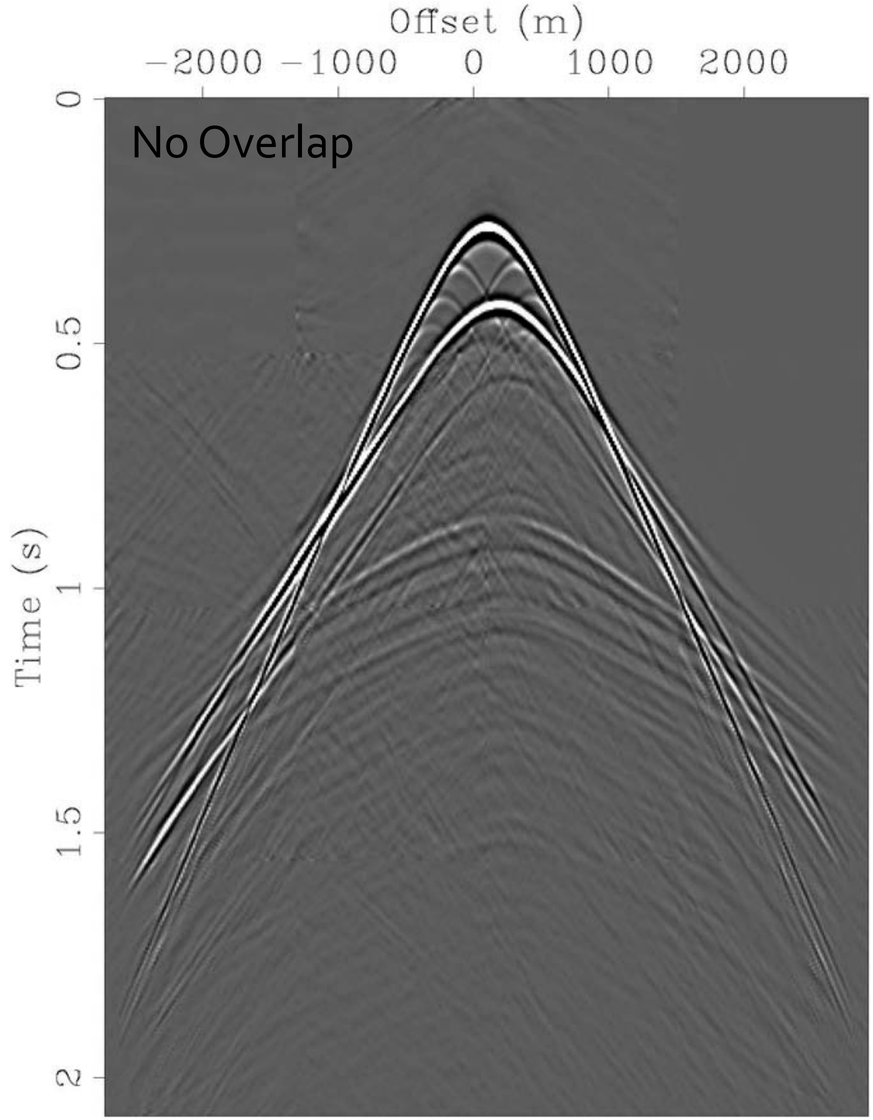
Scenario B

Window	SNR
2X2X2	11.51
2X4X4	11.51
4X4X2	11.47

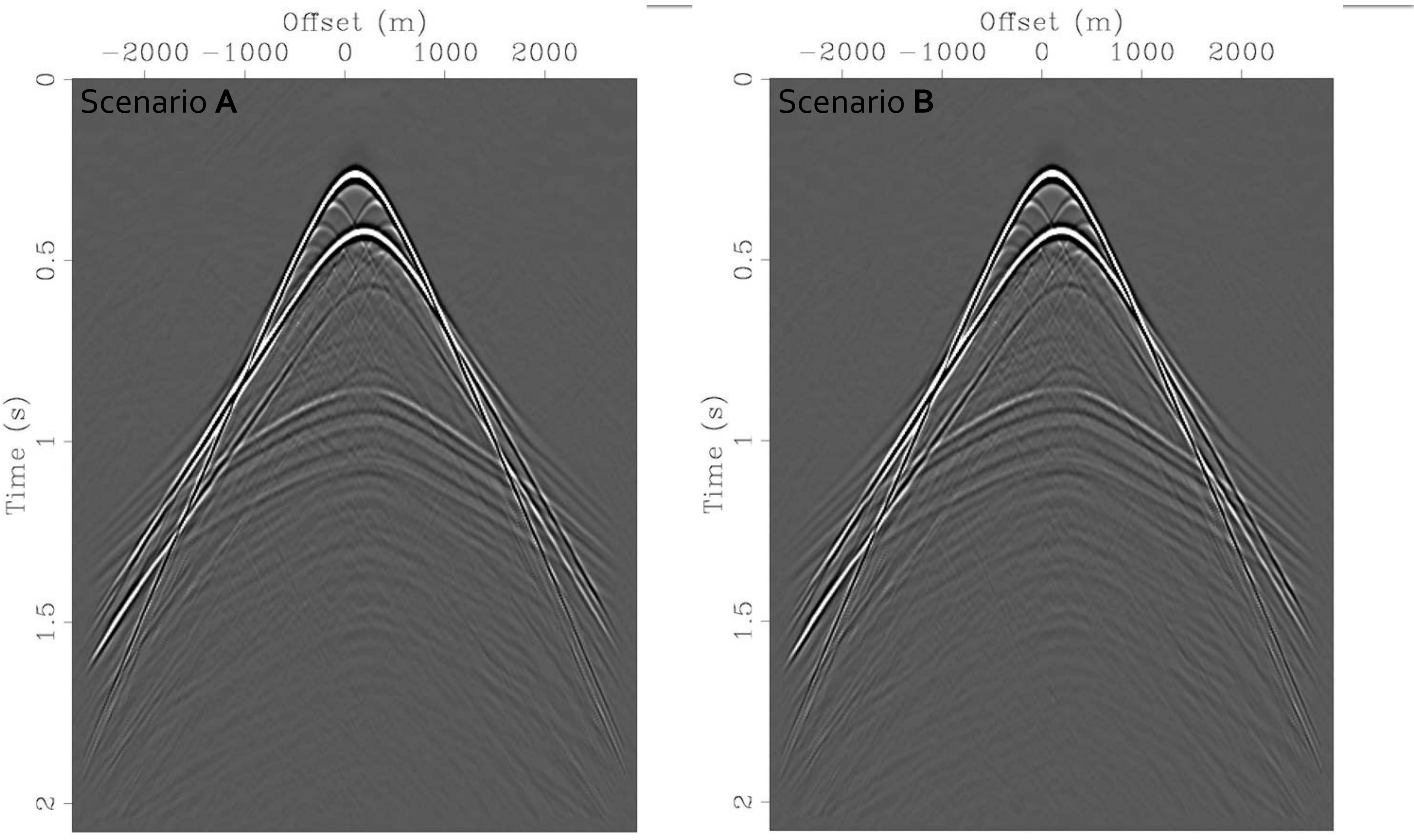
Overlap ε=15

Bayesian based primary-multiple separation (3D)





Bayesian based primary-multiple separation (3D)



Conclusion

- Introduced windowing method to process large data in parallel using the curvelet transform.
- Scenario B performed better in the denoising problem than scenario A due to communicating edges.
- A considerably big advantage of the Bayesian separation, is the ability to use the faster scenario, A, without losing significant data quality.

THANK YOU

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