


Reverse-time Migration Amplitude Recovery with Curvelets



Peyman P. Moghaddam,
Felix Herrmann and Chris Stolk

References

□ **Curvelets and its invariance**

- Curvelet and FIOs, Candes and Demanent (2002)
- Hardy space for FIOs, Smith (1998)

□ **Migration amplitude recovery**

- Optimal scaling for RTM, Symes (2007)
- Illumination based migration, Rickett and Claerbout (2000)
- Hessian Approximation based, Mulder (2003)
- True amplitude migration, Zhang (2003)
- Least square migration, Kuhl and Sacchi (2001)

□ **Optimization methods**

- Soft-thresholding, Donoho (1995)
- Iterative thresholding, Daubechies (2005)
- Gradient based optimization, Nocedal (2001)
- L1 solver (SPGL1), Friedlander(2007)

Overview

- Problem definition
- Imaging as an inversion problem
- Curvelets and their properties
- Curvelets and their invariance under the normal operator
- Diagonal approximation of the normal operator
- Inverse problem reformulation
- Optimization
- Results
- Conclusions

Definition of the Problem

- Basic Imaging problem:

$$\mathbf{d} = \mathbf{K}\mathbf{m} + \mathbf{n}$$

- Desired seismic image characteristics:

- Broad-band
 - Sharp, high resolution
 - 2D curves/3D sheets
- Continuity along the reflectors

- Noise in seismic images

- Random noise
 - Instruments distortion
 - Ambient
- Imaging operator imperfections

Imaging as an Inverse Problem

- Following inversion problem is introduced

$$\min_{\mathbf{m}} J(\mathbf{m}) \text{ subject to } \|\mathbf{d} - \mathbf{K}\mathbf{m}\|_2^2 \leq \epsilon$$

$J(\mathbf{m})$ is a norm or penalty function

- This norm has to
 - promote continuity along reflectors
 - promote sparsity of image in the curvelet domain
 - reduce the artifacts from image
 - enhance the amplitudes of the reflectors
 - remove noise from seismic image

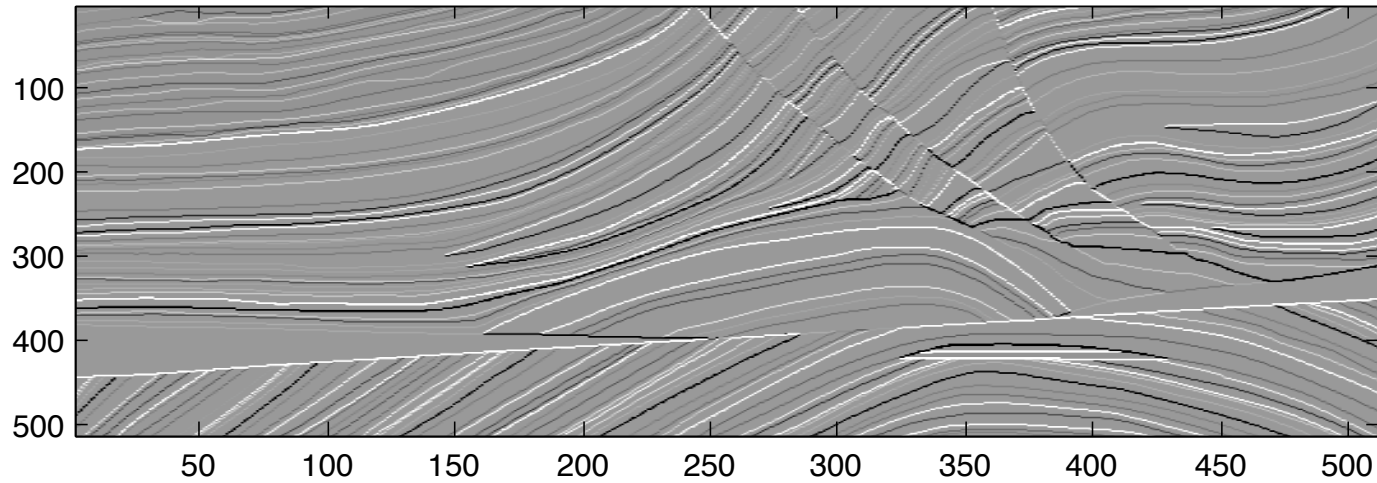
Curvelets and their properties

Curvelets:

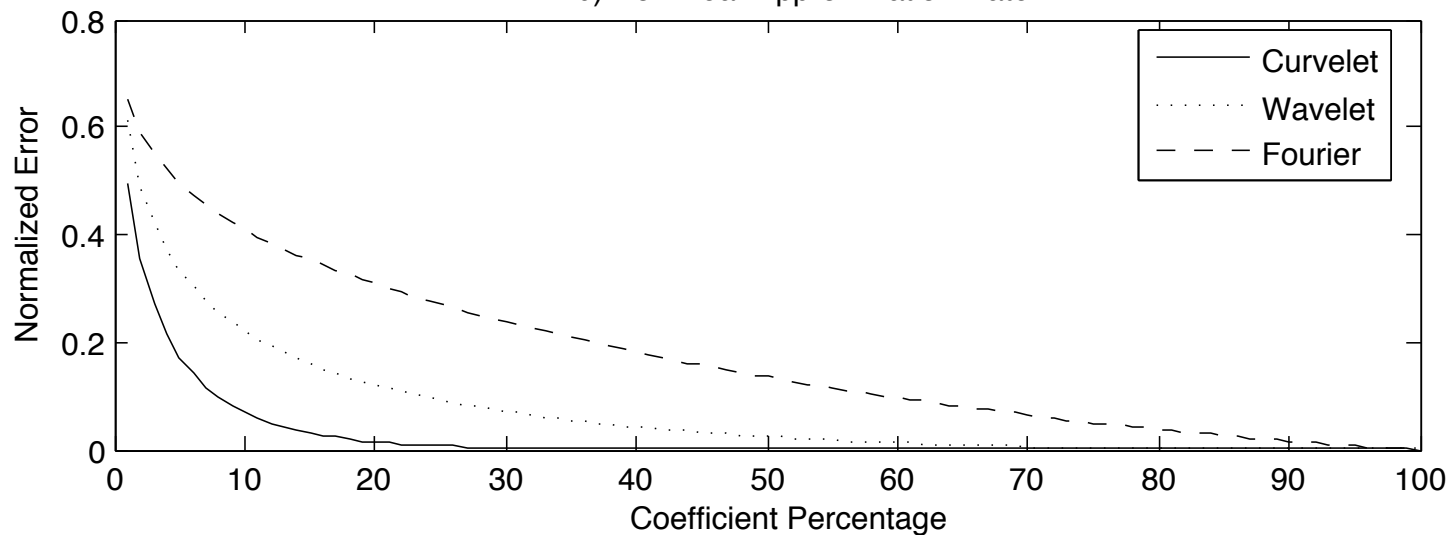
- are multiscale and multi-directional
- sparsely represent seismic images
- are invariant under the action of idealize normal operator
- are constructed as tight frames
- permit a fast transformation
- are used reliably for denoising in image processing applications

Approximation Rate Comparison

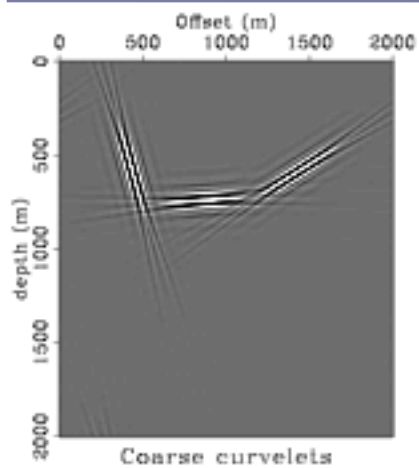
a) Mrmoussi Model



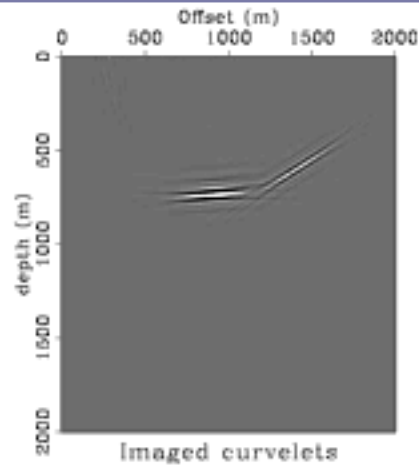
b) Nonlinear Approximation Rate



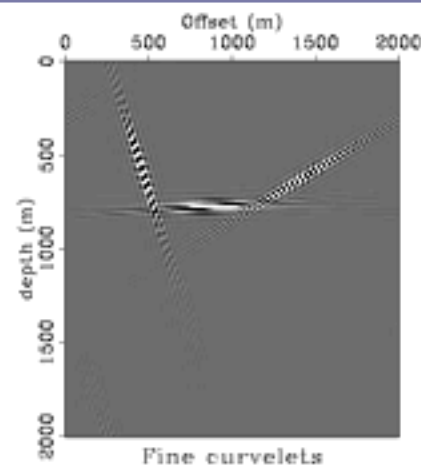
Example (three curvelets)



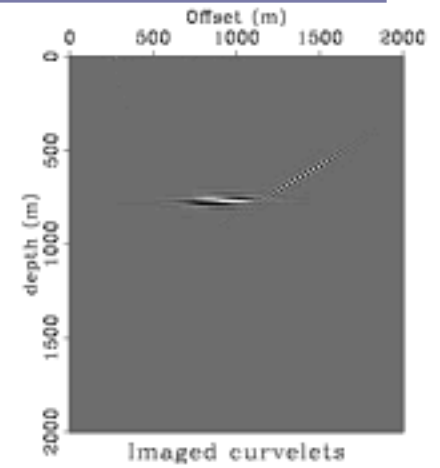
(a)



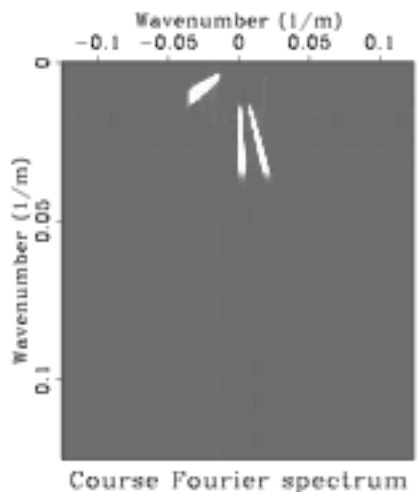
(b)



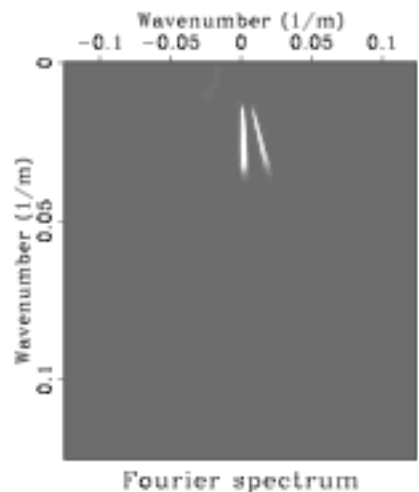
(c)



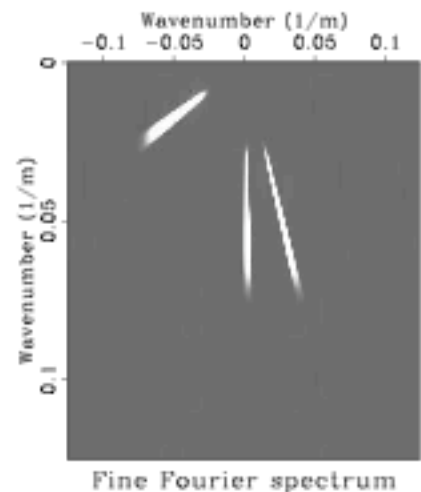
(d)



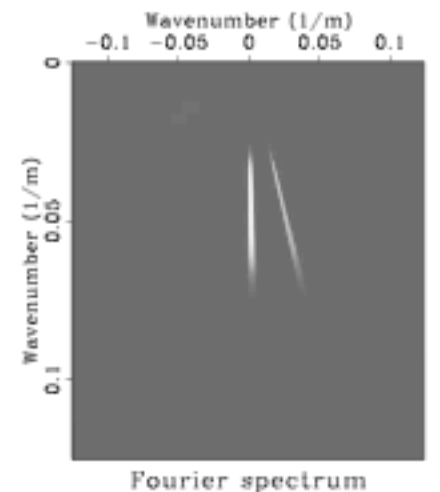
(e)



(f)



(g)



(h)

Normal operator approximation

- ✿ Approximation with curvelet eigenvalue-like decomposition:

$$\mathbf{C}^T \mathbf{D}_\Psi \mathbf{C} \approx \mathbf{K}^T \mathbf{K}$$

- Diagonal matrix is smooth in phase space (in the curvelet domain) for smooth background velocity models
- Computationally cheap, requires only “one” evaluation of the normal operator to estimate the diagonal scaling

Diagonal Approximation

- Approximation with curvelet regularization,

$$\mathbf{C}^T \mathbf{D}_\Psi \mathbf{C} \approx \mathbf{K}^T \mathbf{K}$$

- Positivity constraint on diagonal estimation,

$$\min_{\mathbf{u}} (\|\mathbf{K}^T \mathbf{K} \mathbf{r} - \mathbf{C}^T \text{diag}(e^{\mathbf{u}}) \mathbf{C} \mathbf{r}\|_2^2 + \lambda \|L e^{\mathbf{u}}\|_2^2)$$

$$\mathbf{L} = [\mathbf{D}_x^T \quad \mathbf{D}_y^T \quad \mathbf{D}_\theta^T]^T \quad \mathbf{D}_\Psi = \text{diag}(e^{\mathbf{u}})$$

- Solve using quasi-Newton method
- Explore smoothness along the curvelet symbol
- Computationally cheap, requires only “one” evaluation of normal operator

Problem reformulation

- Forming the normal equation,

$$\begin{aligned}\mathbf{d} = \mathbf{K}\mathbf{m} + \mathbf{n} &\Rightarrow \mathbf{K}^T \mathbf{d} = \mathbf{K}^T \mathbf{K}\mathbf{m} + \mathbf{K}^T \mathbf{n} \\ &\Rightarrow \mathbf{y} \approx \mathbf{A}\mathbf{A}^T \mathbf{m} + \mathbf{e} \\ &= \mathbf{A}\mathbf{x}_0 + \mathbf{e}\end{aligned}$$

- with

$$\mathbf{y} = \mathbf{K}^T \mathbf{d}, \quad \mathbf{A} = \mathbf{C}^T \sqrt{\mathbf{D}_\Psi}$$

- \mathbf{A} is *scaled* the inverse curvelet transform

Recovery Problem Formulation

$$\mathbf{P}_\epsilon : \begin{cases} \tilde{\mathbf{x}} = \min_{\mathbf{x}} J(\mathbf{x}) & \text{subject to } \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2 \leq \epsilon \\ \tilde{\mathbf{m}} = (\mathbf{A}^T)^\dagger \tilde{\mathbf{x}}. \end{cases}$$

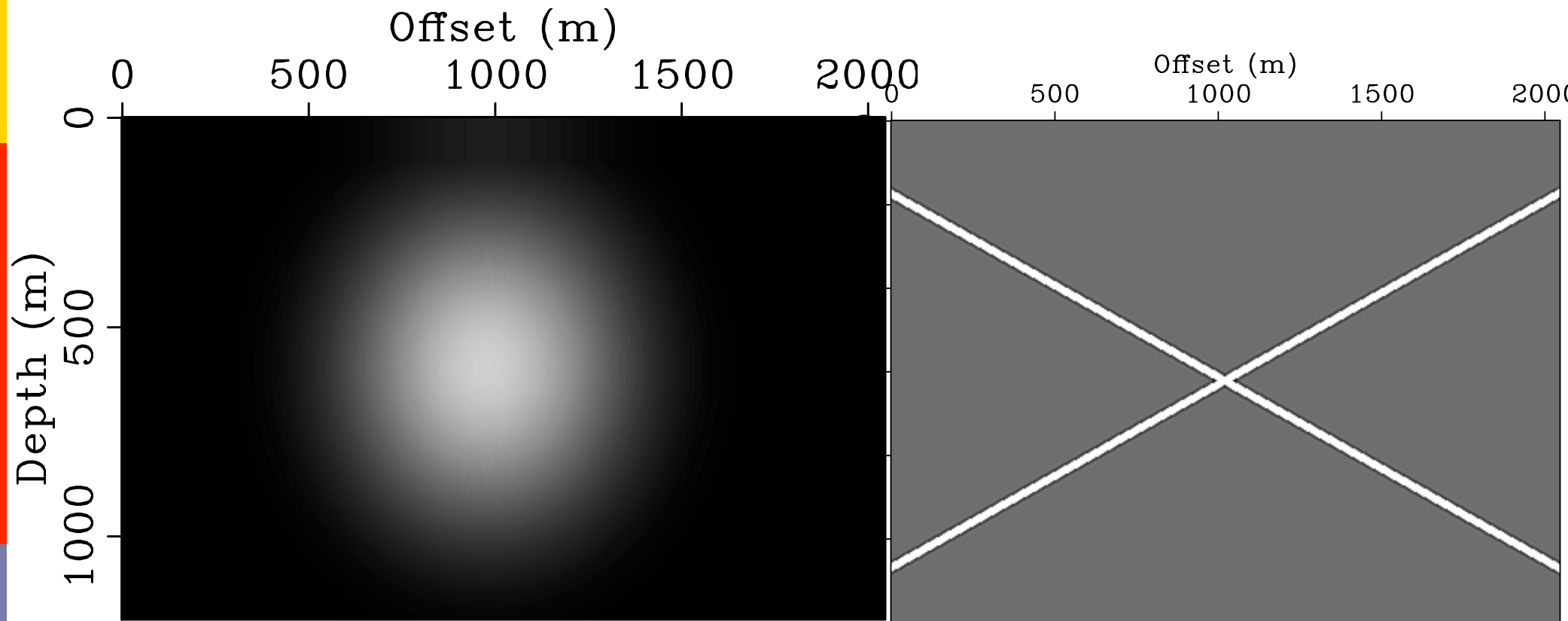
- With $J(\mathbf{x}) = \|\mathbf{x}\|_1$
- $J(\mathbf{x})$ promotes sparsity on the weighted curvelet coefficients of the reflectivity

Recovery Method

- Form the normal operator $\mathbf{K}^T \mathbf{K}$.
- Select a reference vector that is close to the unknown image.
- Estimate the diagonal. (*i.e.*, \mathbf{D}_μ)
- Construct the matrix $\mathbf{A} = \mathbf{C}^T \sqrt{\mathbf{D}_\mu}$.
- Solve L1 optimization problem to find the solution for the reflectivity.

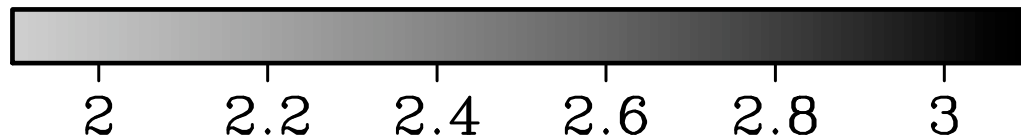
Conflicting-dips example

Linearized Born modeled Data



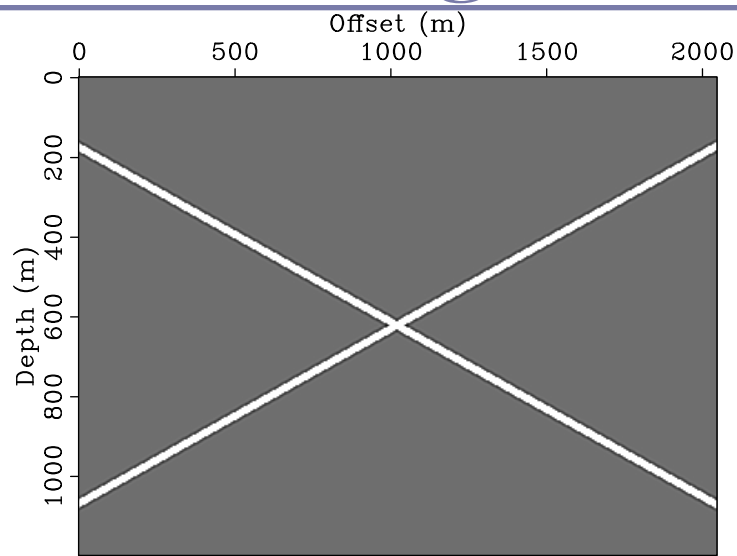
Lens Velocity Model

Reflectivity

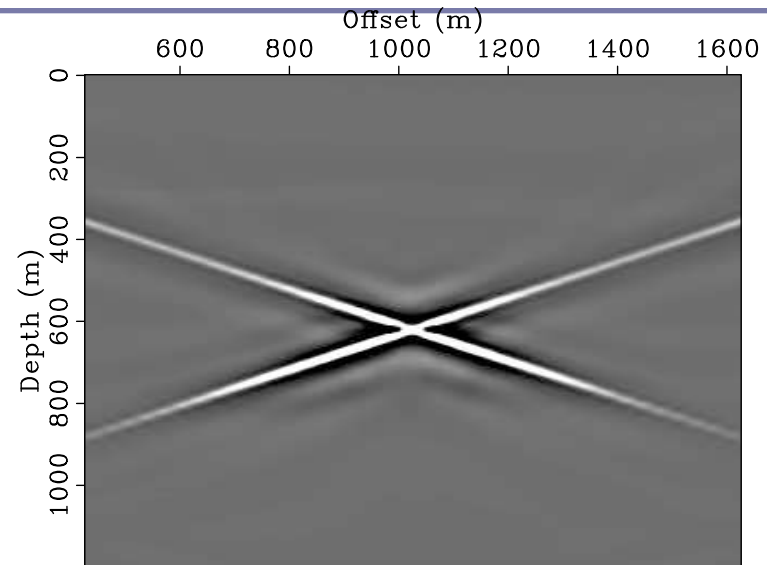


Conflicting-dips example

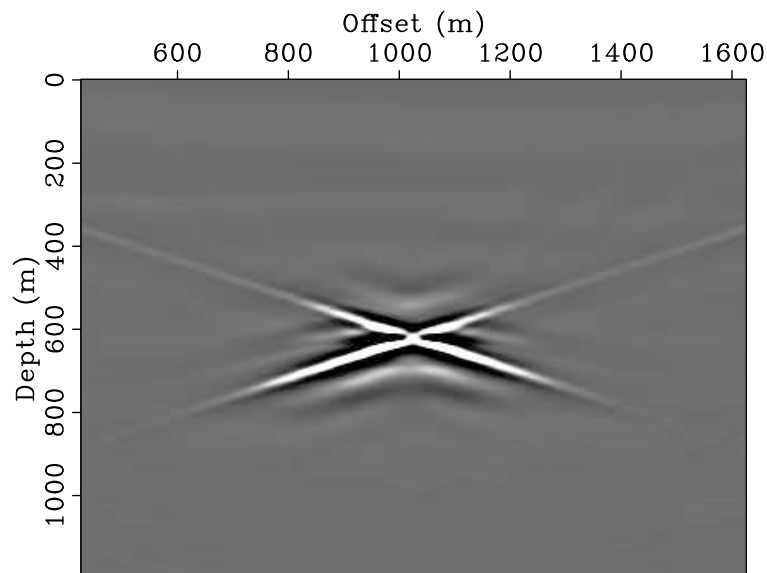
Diagonal approximation



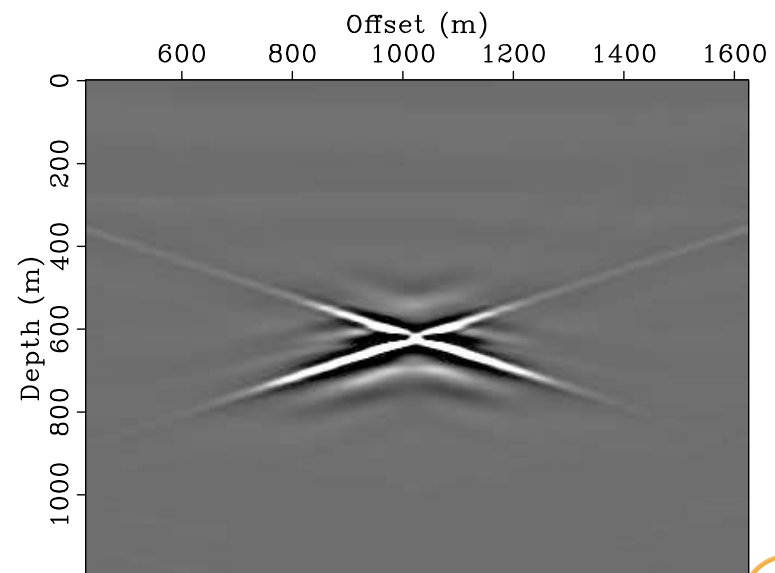
Reflectivity



Migrated Image



Remigrated

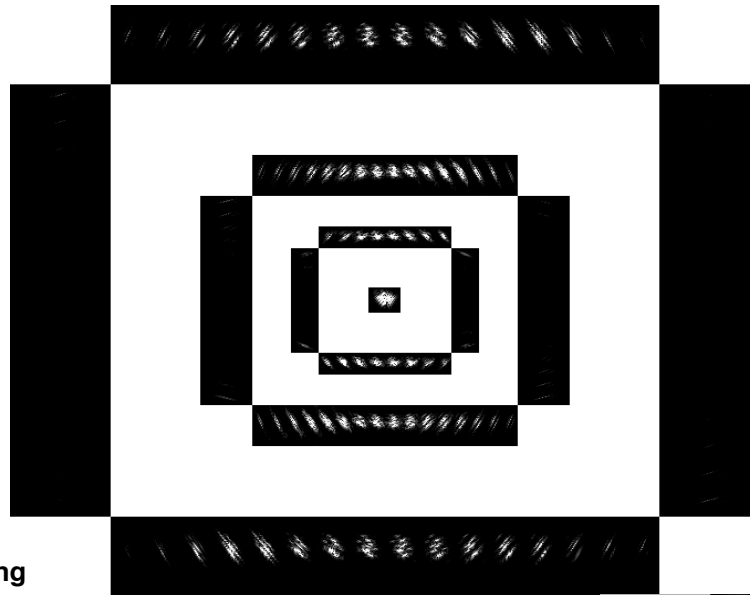


Approximate Remigrated

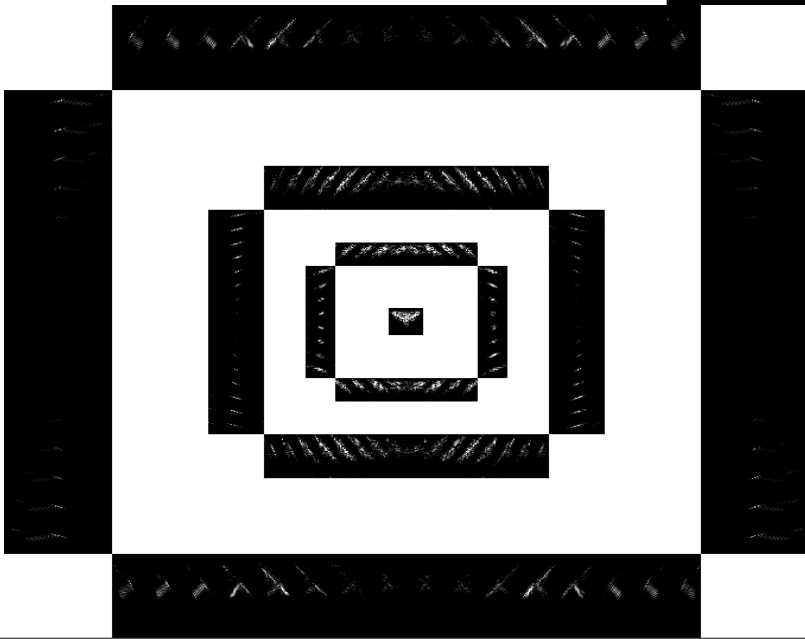
Example

Curvelet Mosaic Plot

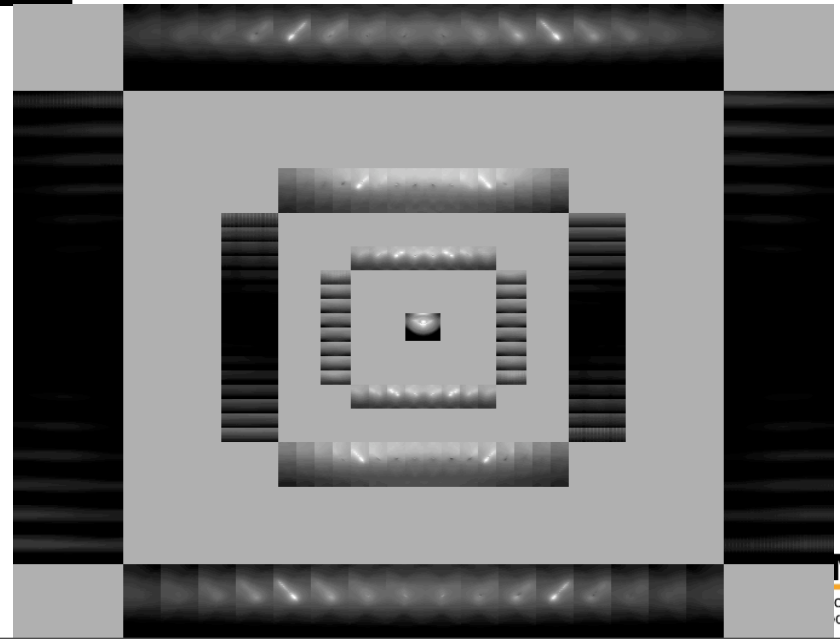
Model in Curvelet Domain



Diagonal Before Smoothing

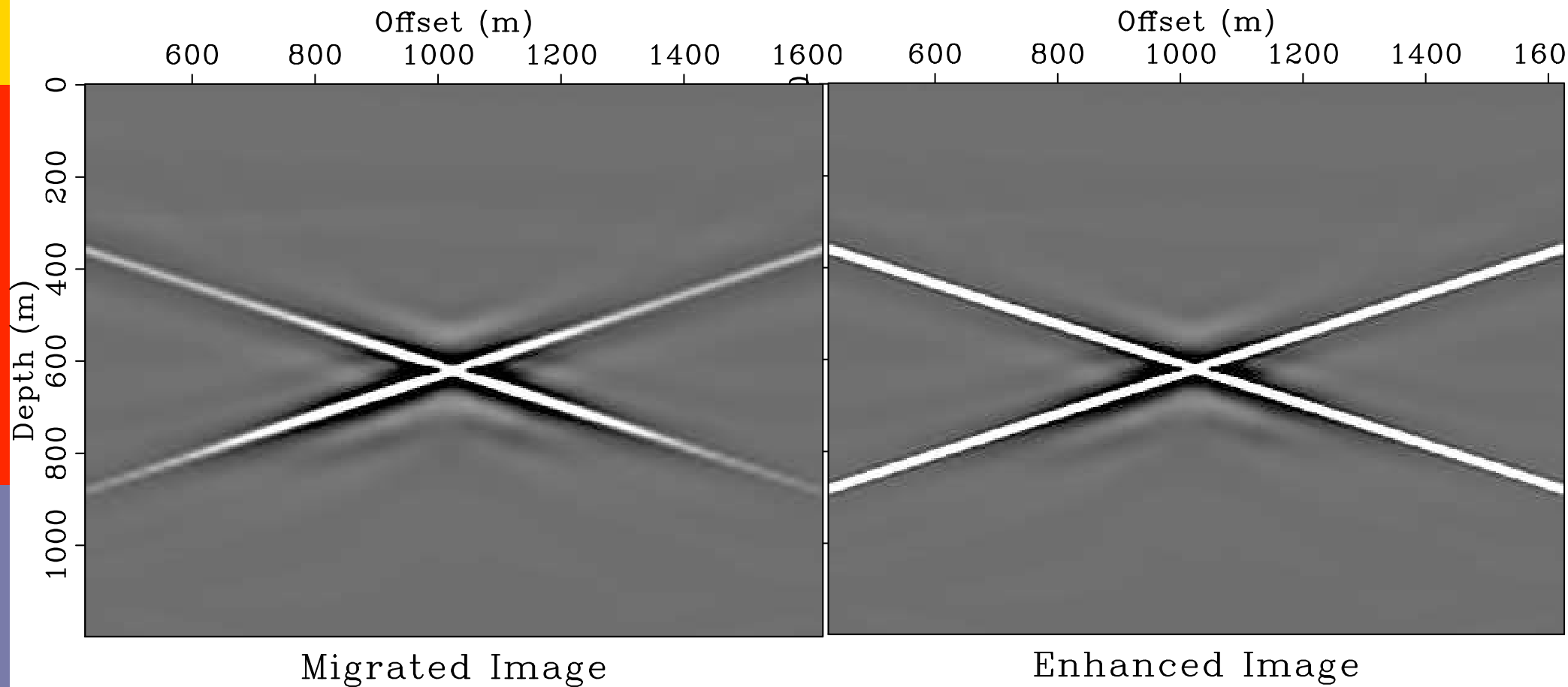


Diagonal After Smoothing



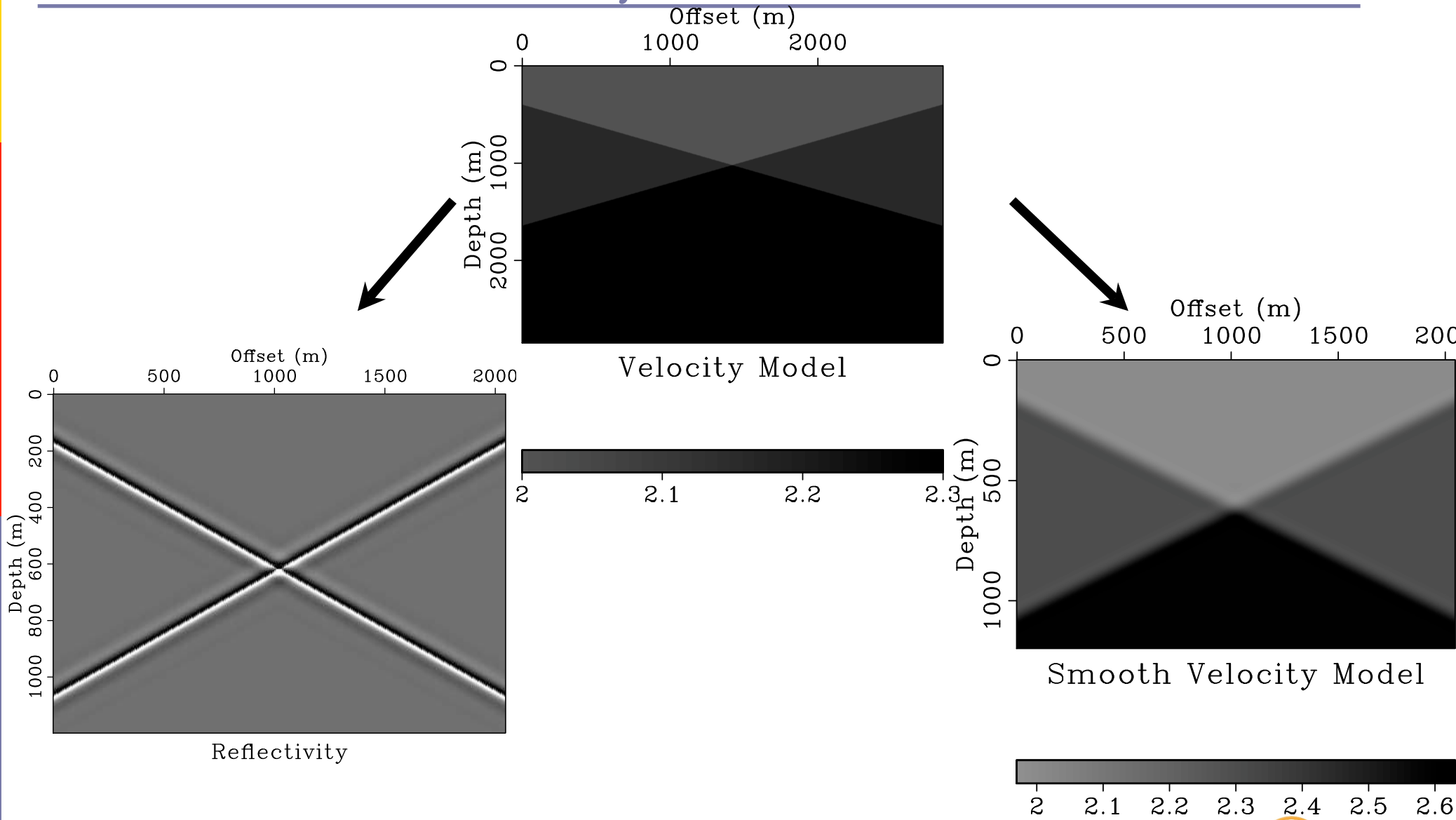
Conflicting-dips example

Result



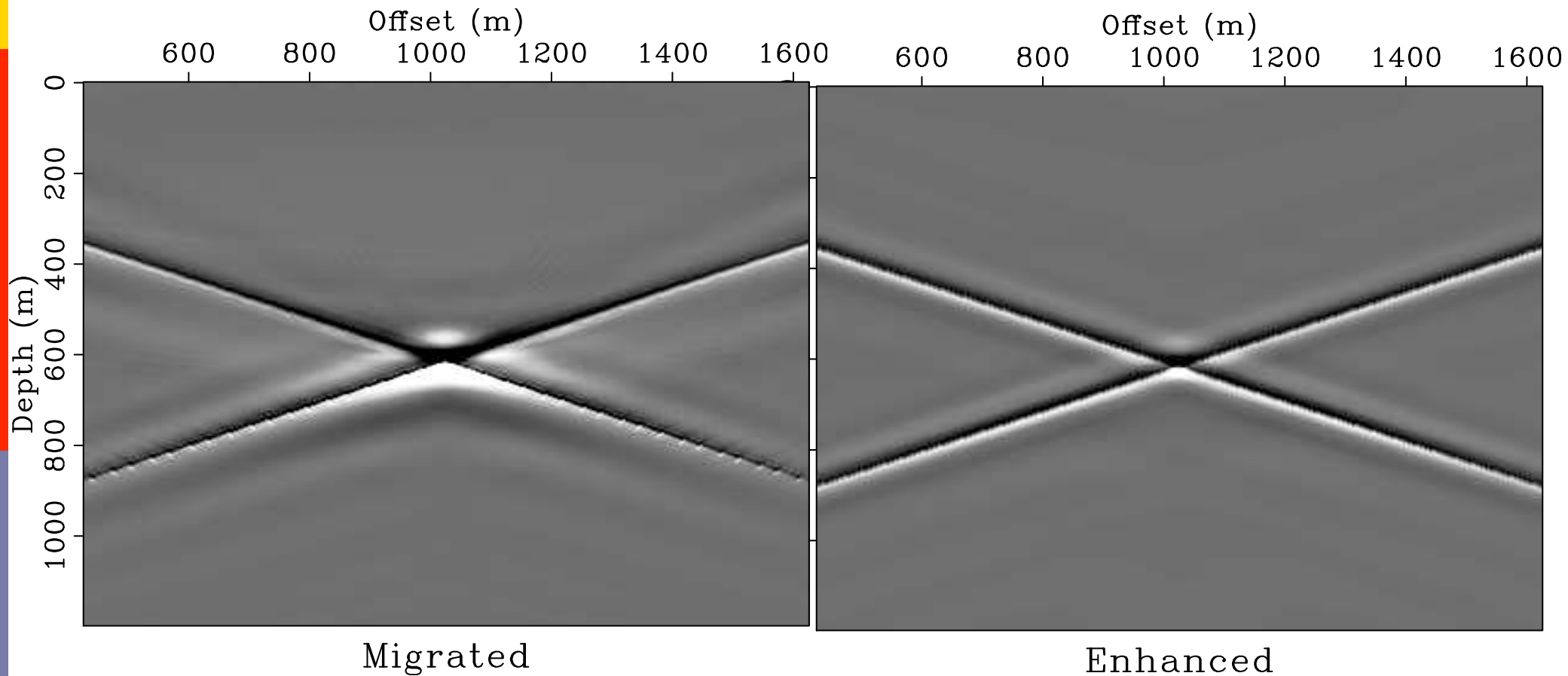
Conflicting-dips example

Full synthetic data



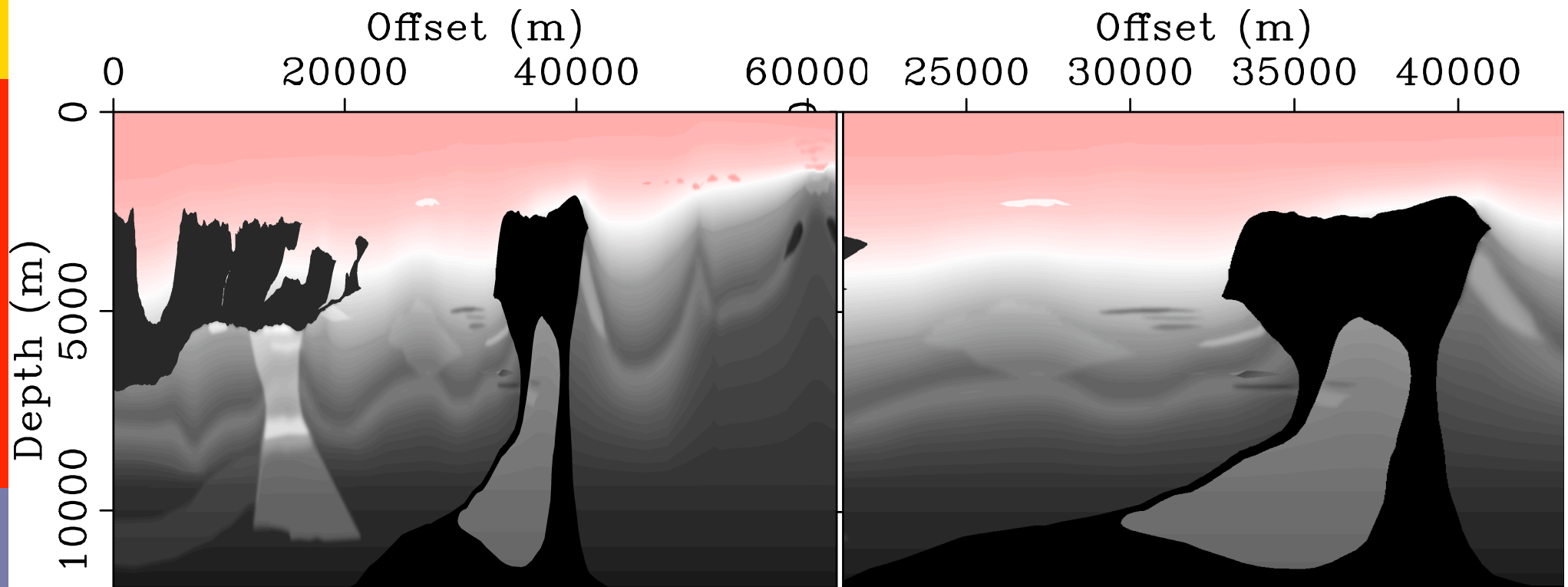
Conflicting-dips example

Full synthetic data

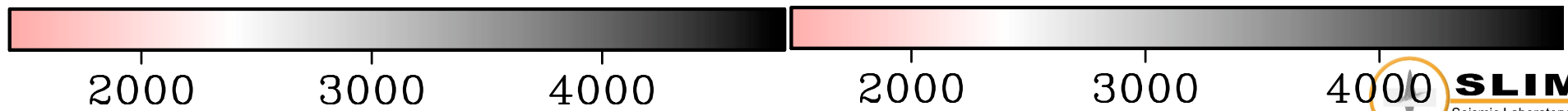


BP-dataset example

Velocity Model



BP Velocity Model



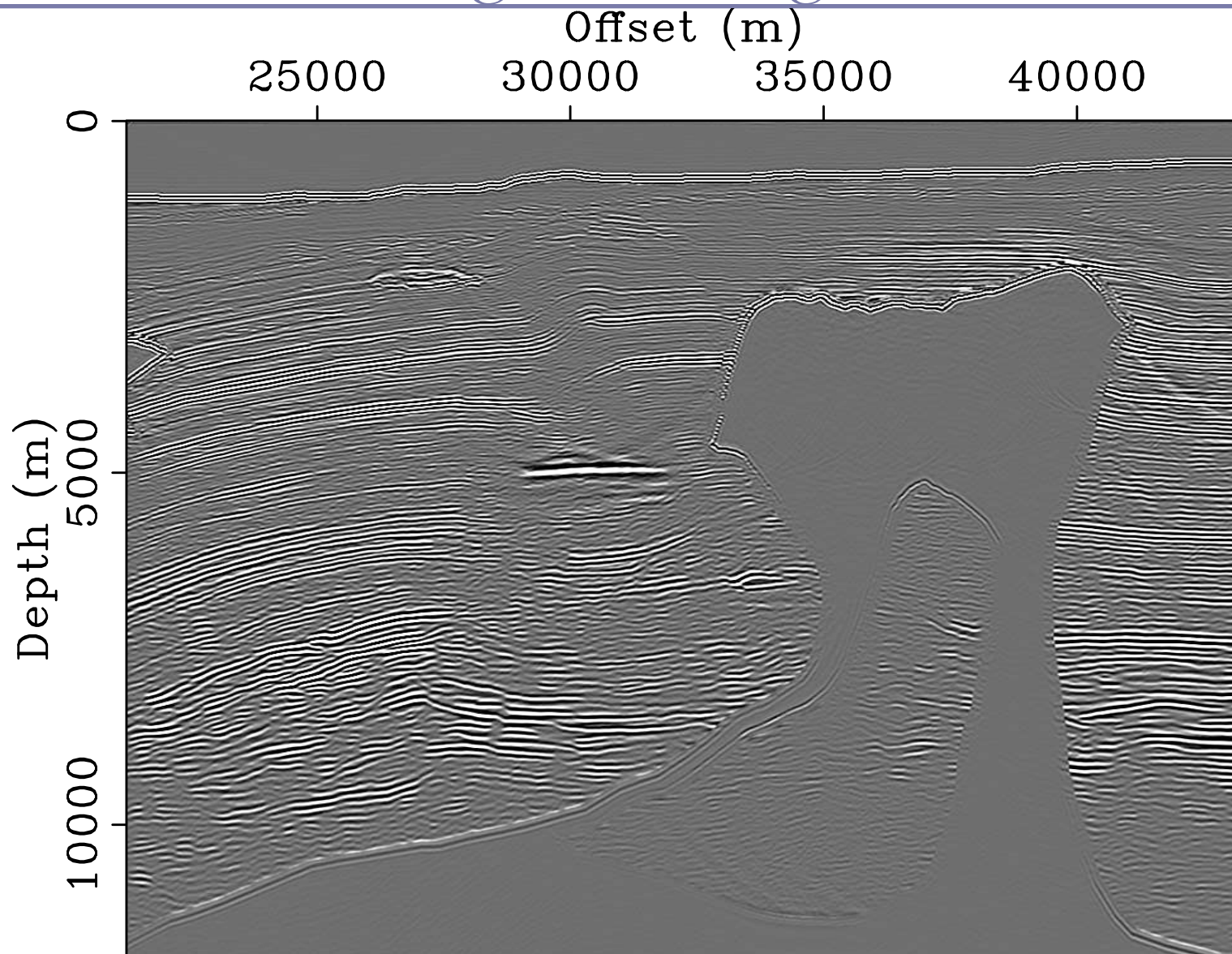
BP-dataset example

Description

- Dataset with
 - ...streamer configuration
 - ...15 (km) streamer and 12.5 (m) group interval and 50 (m) shot interval
 - ...14 (s) of recording time with 6 (ms) sampling interval
 - ...total of 1340 shots and 1201 receivers
- Pre-processing steps:
 - free surface waves (direct arrivals) are removed
 - free surface multiple are removed (using SRME)
 - dipping waves are removed using band pass filtering
 - background velocity is smoothed
 - both migrated and re-migrated images were corrected for illumination map

BP-dataset example

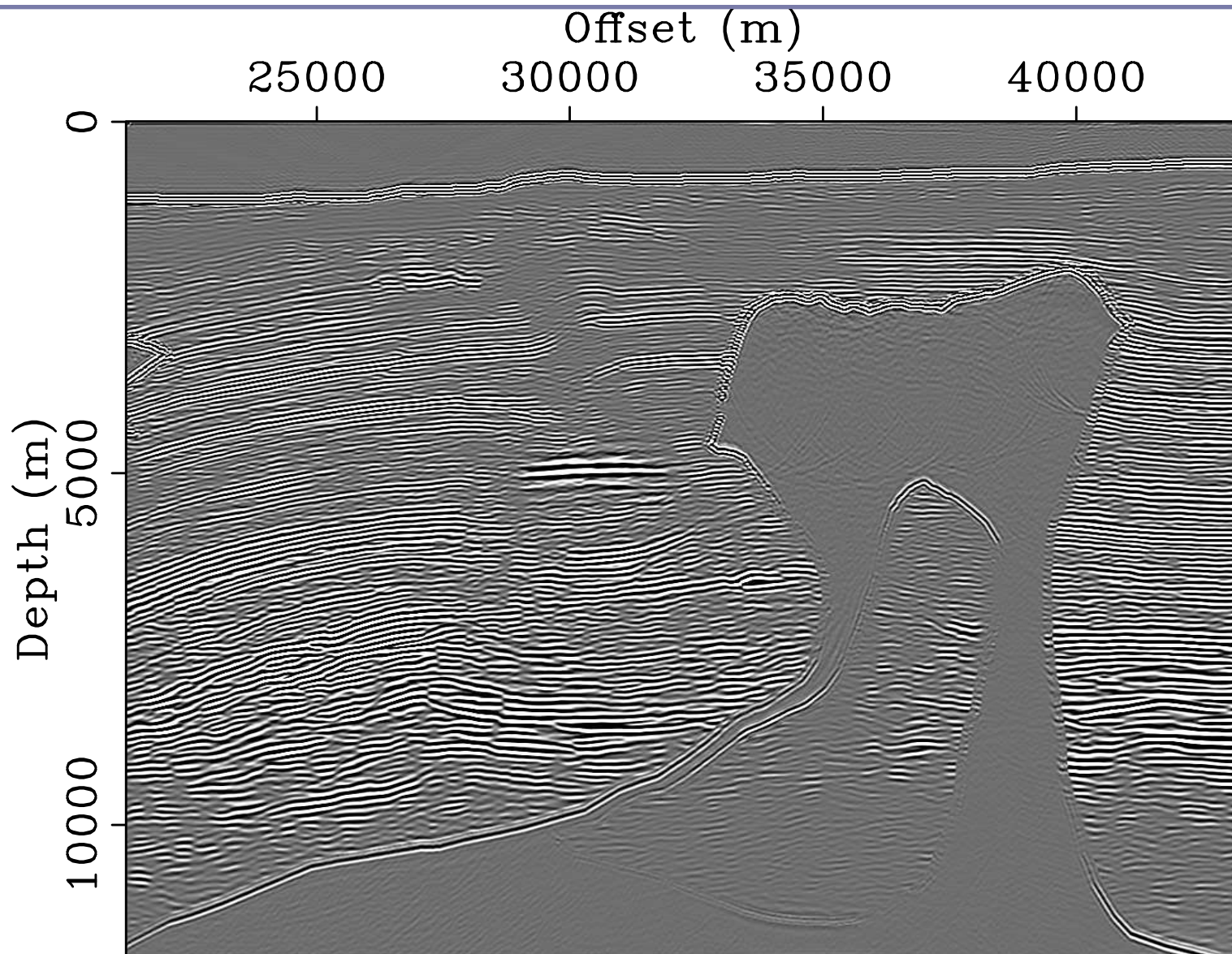
migrated image



Migrated

BP-dataset example

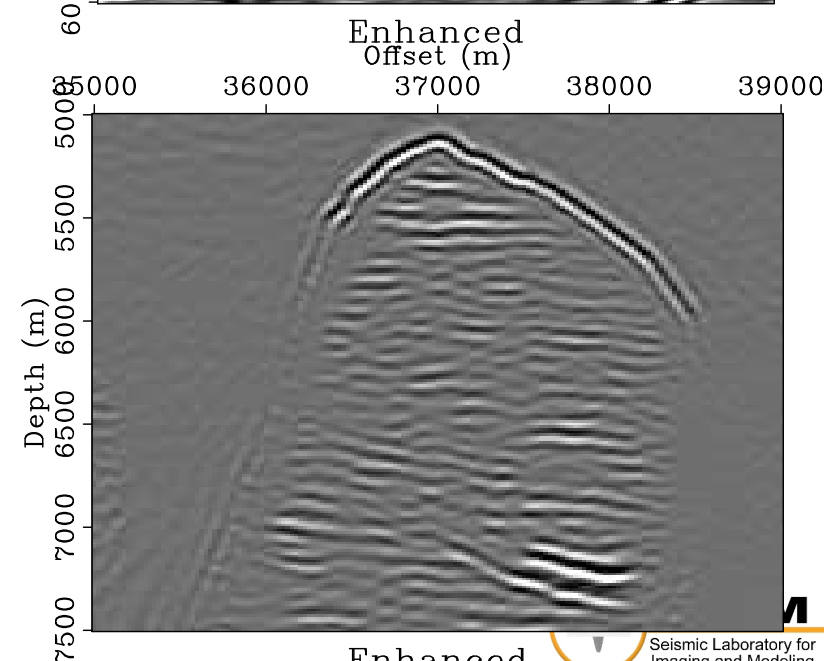
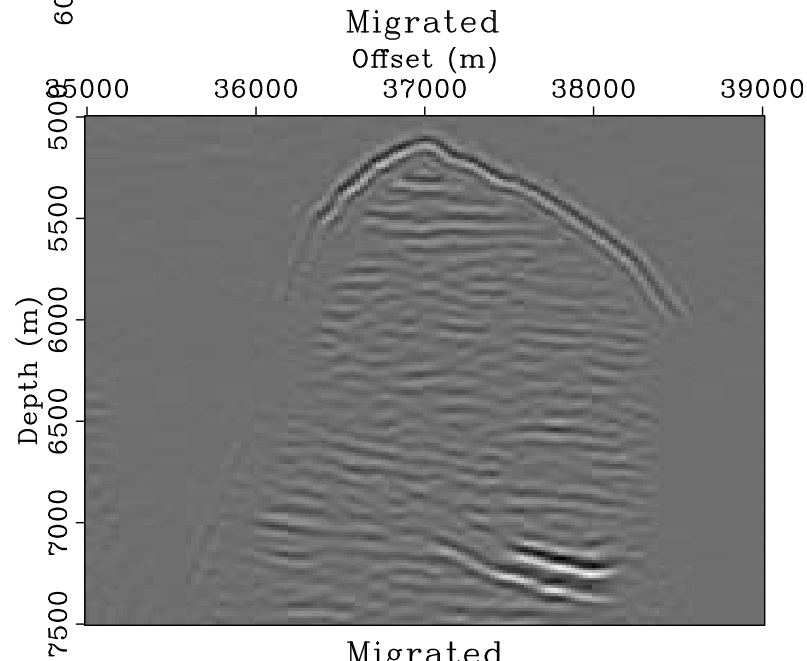
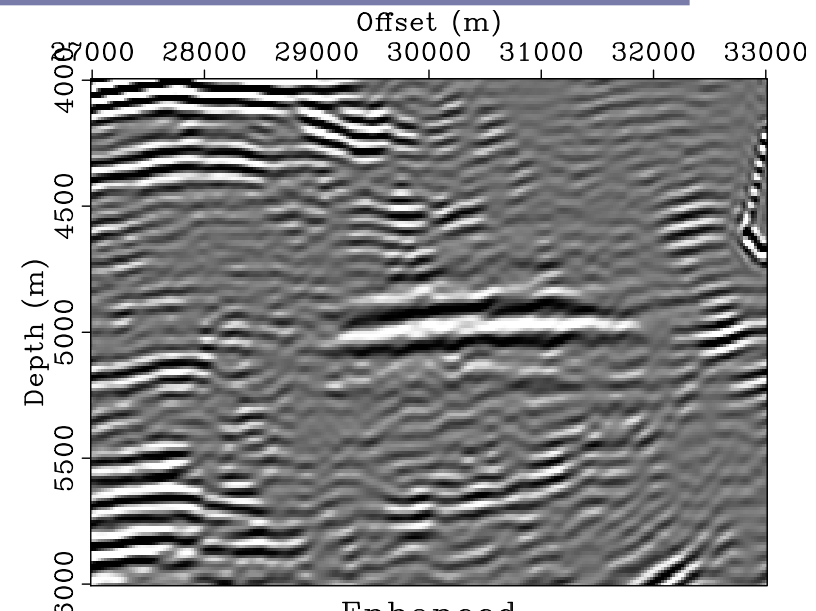
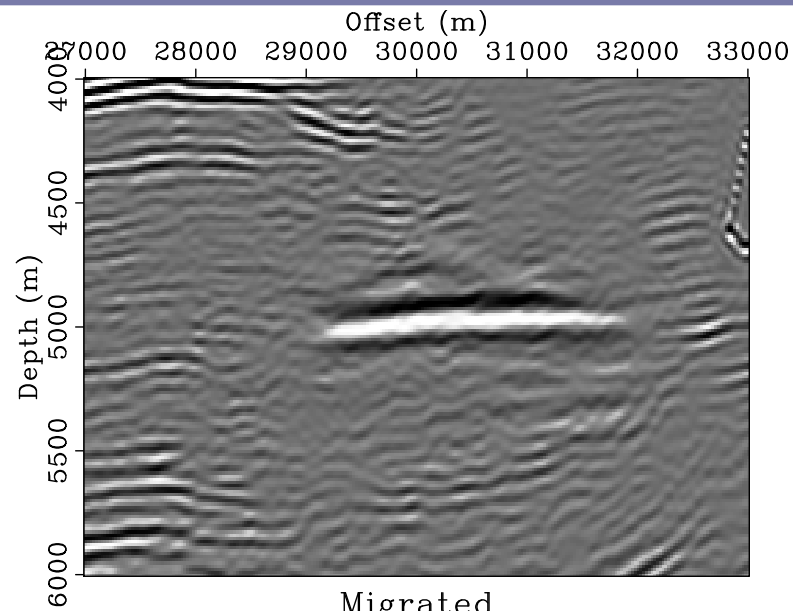
amplitude-corrected migrated image



Enhanced

BP-dataset example

zoomed comparisons



Conclusion

This work

- ... introduces a novel approach to migration amplitude recovery
- ... employs an accurate diagonal decomposition of the expensive normal operator
- ... employs curvelets as essential elements in both approximation and estimation
- ... can be used instead of illumination map or in conjunction with it

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