

# Focused recovery with the curvelet transform

joint work with  
Deli Wang  
(visitor from Jilin university)  
and  
Gilles Hennenfent



# Focal transform with curvelets

joint work with Deli Wang (visitor from Jilin university) and Gilles Hennenfent



## Focused recovery

**Non-data-adaptive** Curvelet Reconstruction with Sparsity-promoting Inversion (CRSI) derives from **sparsity** of seismic data.

Berkhout and Verschuur's **data-adaptive** Focal transform derives from **focusing** of seismic data by the major primaries.

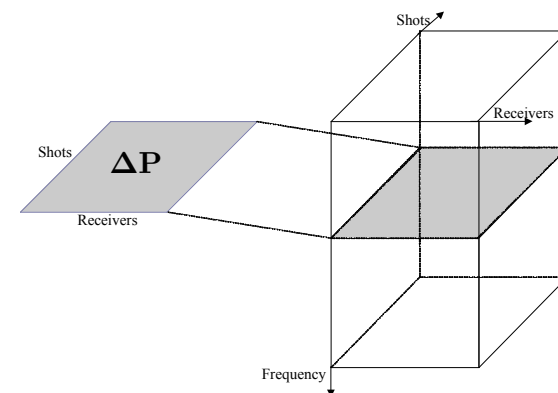
Both approaches entail the **inversion** of a linear operator.

Combination of the two yields

- improved focusing => more sparsity
- curvelet sparsity => better focusing



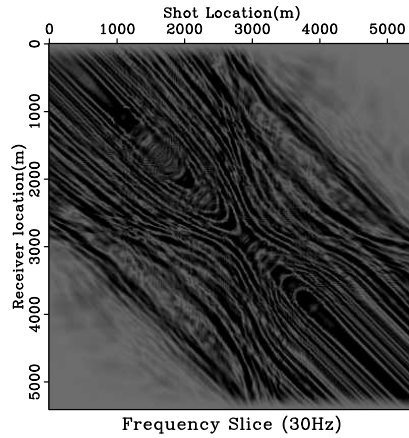
## Primary operator



Frequency slice from data matrix with dominant primaries.



## Primary operator



## Primary operator

**Primaries to first-order multiples:**

$$\Delta \mathbf{p} \mapsto \mathbf{m}^1 = (\Delta \mathbf{P} \mathcal{A} *_{t,x} \Delta \mathbf{p})$$

**First-order multiples into primaries:**

$$\mathbf{m}^1 \mapsto \Delta \mathbf{p} \approx (\Delta \mathbf{P} \mathcal{A} \otimes_{t,x} \Delta \mathbf{p})$$

**with the acquisition matrix**

$$\mathcal{A} = (\mathcal{S}^\dagger \mathbf{R} \mathcal{D}^\dagger)$$

**“inverting” for source and receiver wavelet wavelets geometry and surface reflectivity.**

## Curvelet-based Focal transform

Solve

$$\mathbf{P}_\epsilon : \begin{cases} \tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 & \text{s.t. } \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2 \leq \epsilon \\ \tilde{\mathbf{f}} = \mathbf{S}^T \tilde{\mathbf{x}} \end{cases}$$

with

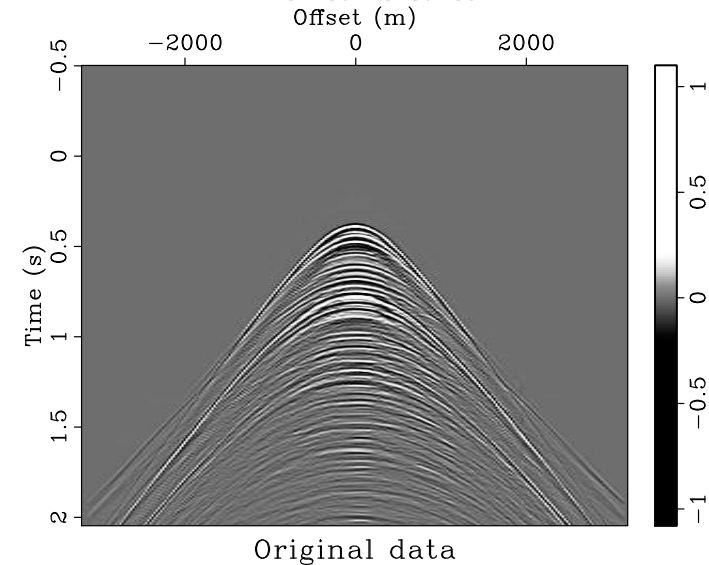
$$\mathbf{A} := \Delta \mathbf{P} \mathbf{C}^T \quad \text{and} \quad \Delta \mathbf{P} := \mathbf{F}^H \text{block diag}\{\Delta\} \mathbf{F}$$

$$\mathbf{S} := \mathbf{C}$$

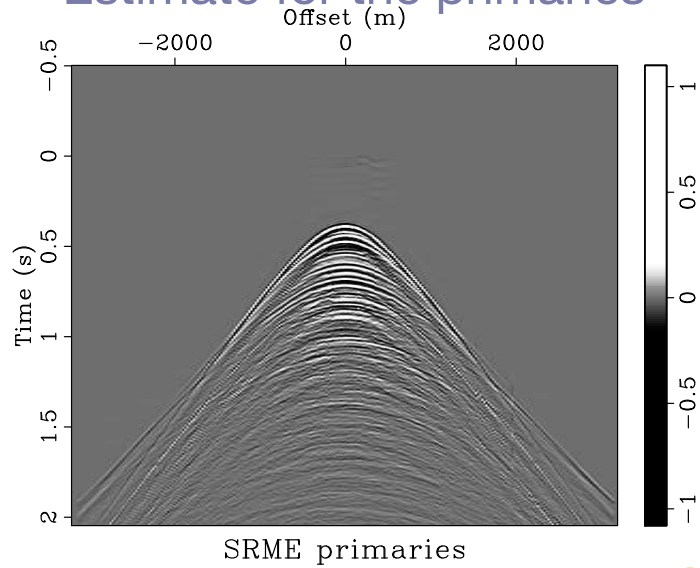
$$\mathbf{y} = \mathbf{P}(:,)$$

$$\mathbf{P} = \text{total data.}$$

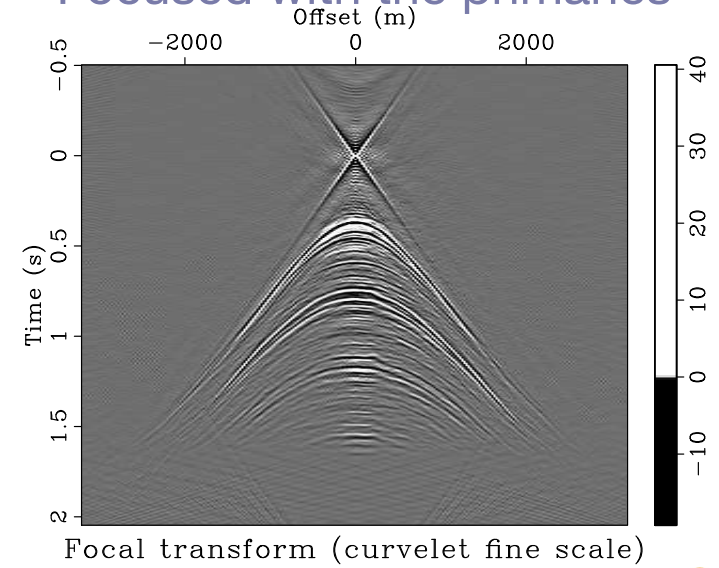
## Total data



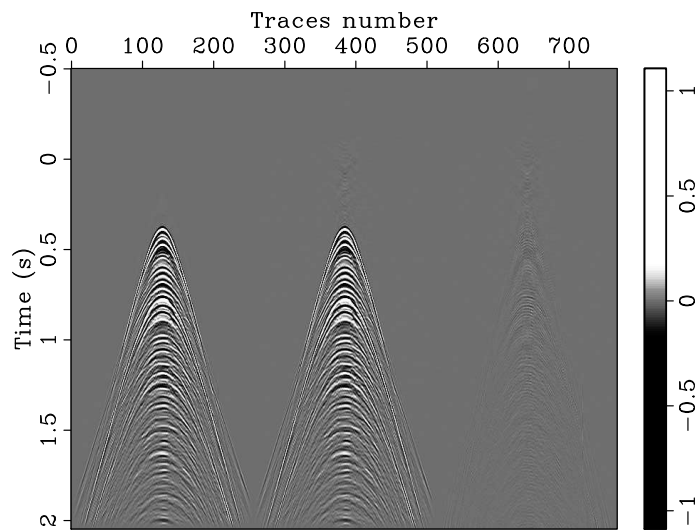
## Estimate for the primaries



## Focused with the primaries



## Difference



## Recovery with focussing

Solve

$$\mathbf{P}_\epsilon : \begin{cases} \tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 & \text{s.t. } \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2 \leq \epsilon \\ \tilde{\mathbf{f}} = \mathbf{S}^T \tilde{\mathbf{x}} \end{cases}$$

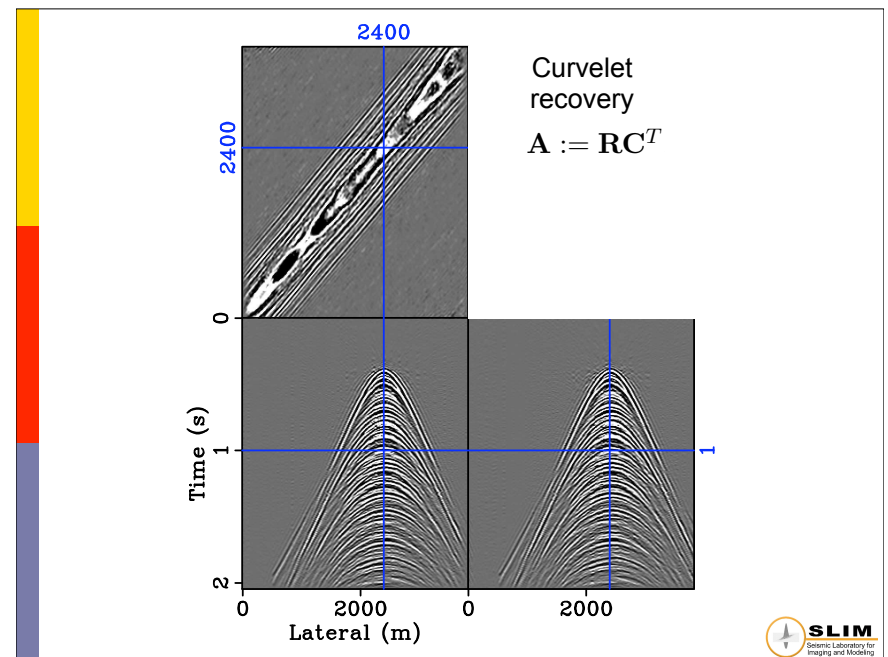
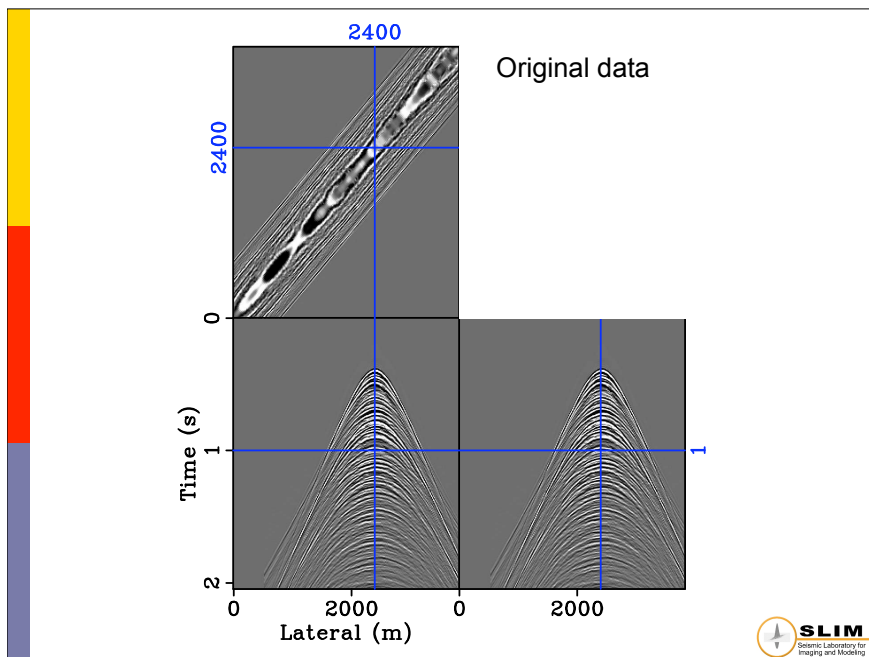
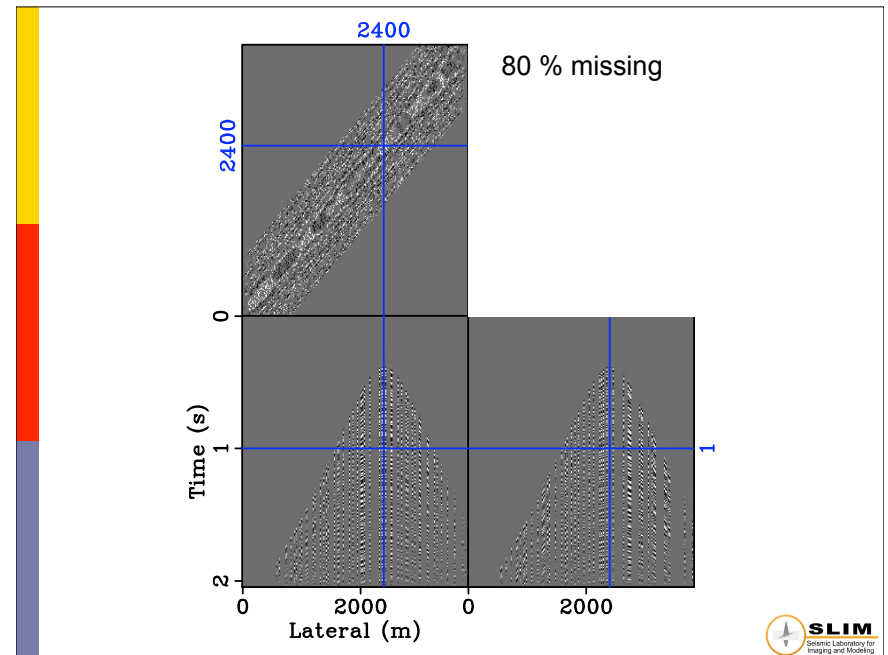
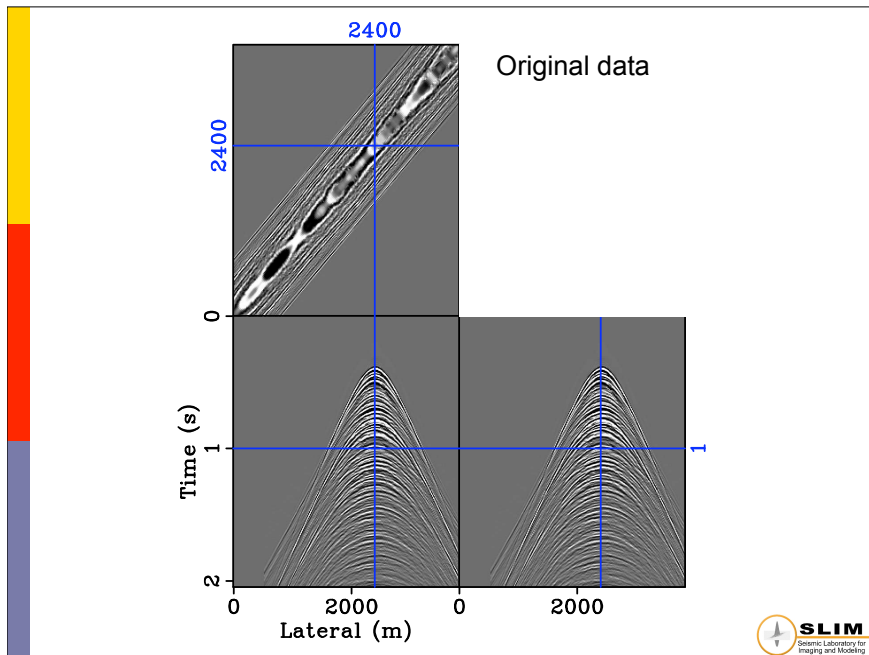
with

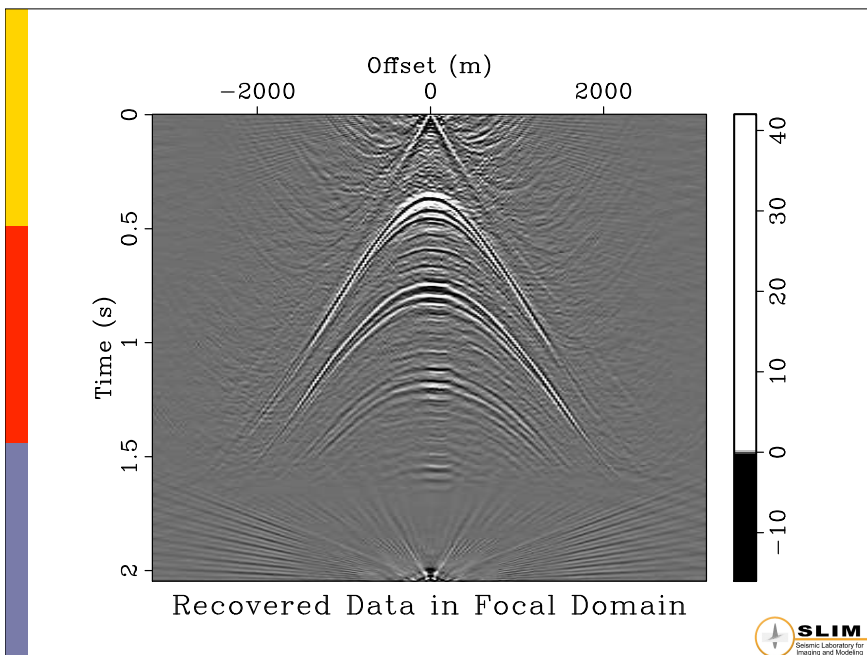
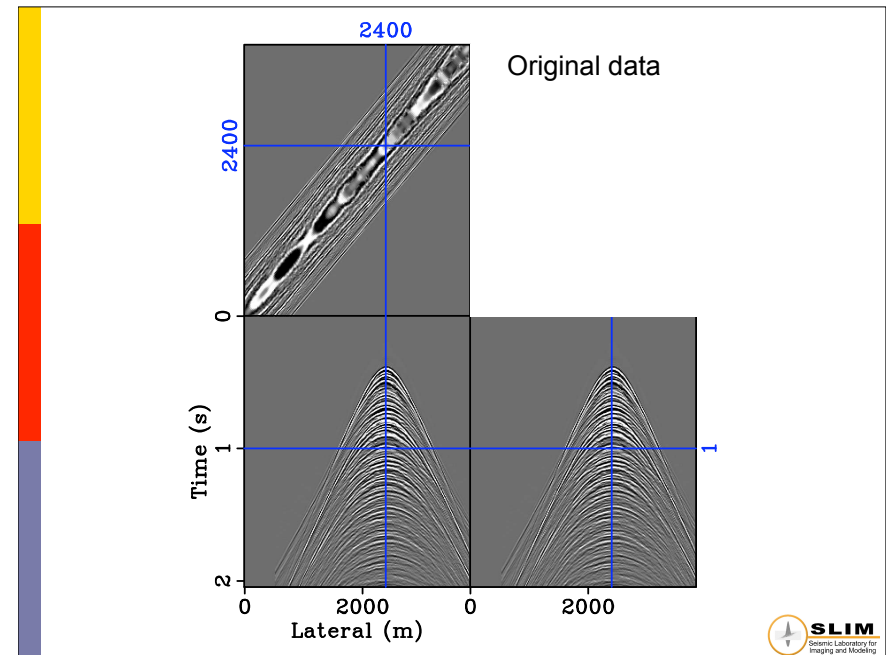
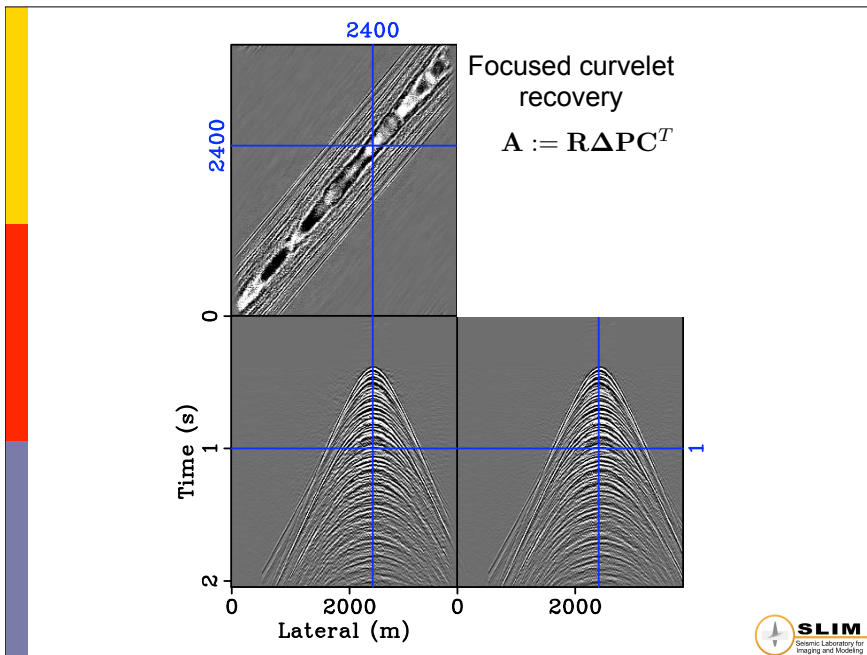
$$\mathbf{A} := \mathbf{R}\Delta\mathbf{P}\mathbf{C}^T$$

$$\mathbf{S}^T := \Delta\mathbf{P}\mathbf{C}^T$$

$$\mathbf{y} = \mathbf{R}\mathbf{P}(:)$$

$$\mathbf{R} = \text{picking operator.}$$





## Observations

Focal transform

- allows for incorporation of a priori information
- is reminiscent of an imaging operator
- works because of addition compression and incoherence
- leads to an improved recovery

Outlook

- Restriction corresponds to a compression of the operator
- Opens the way to migration-based recovery
- or a more "blue sky" approach of compressive wavefield extrapolation

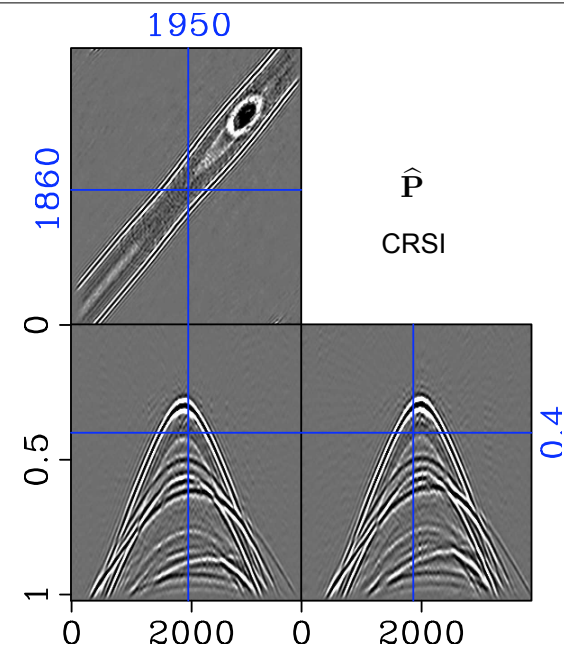
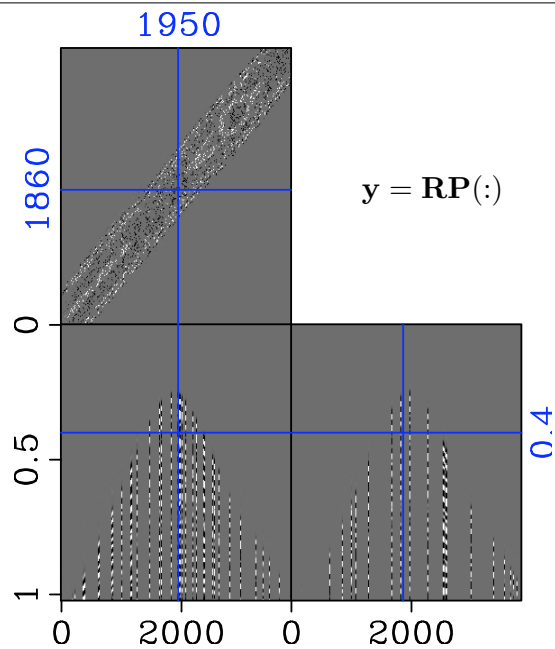
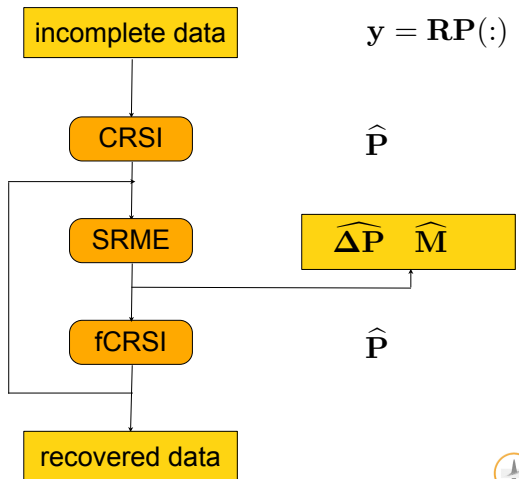
SLIM  
 Seismic Laboratory for Imaging and Monitoring

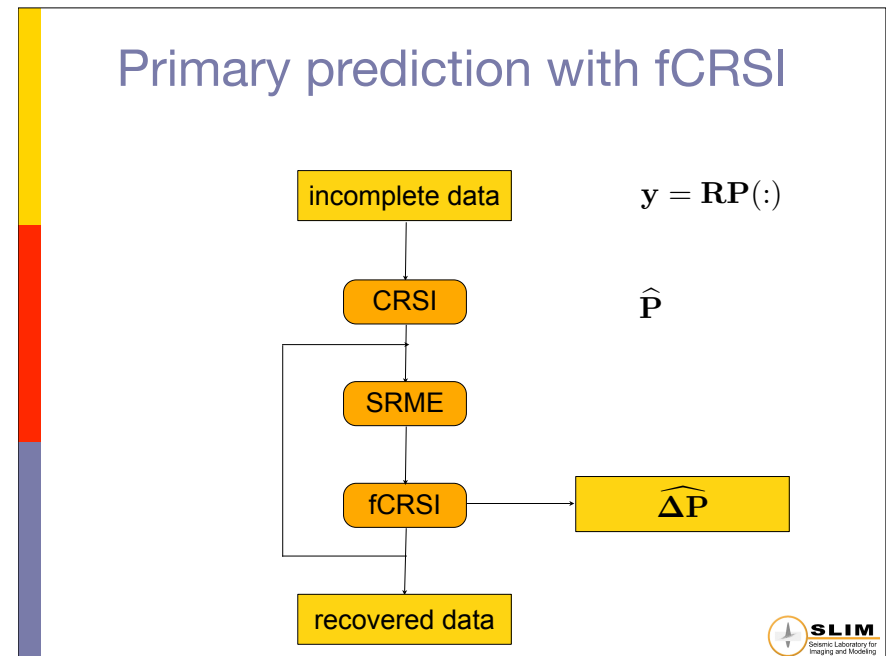
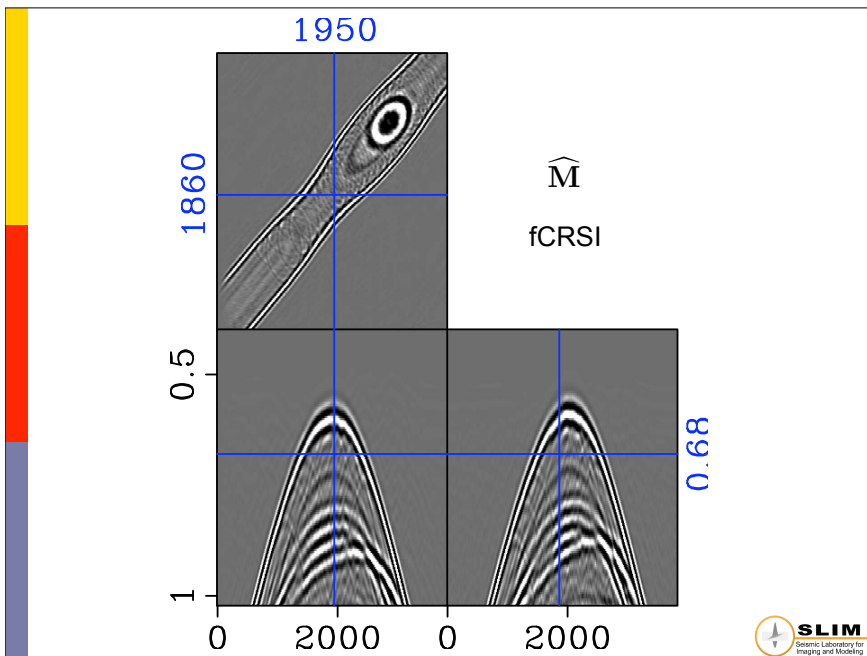
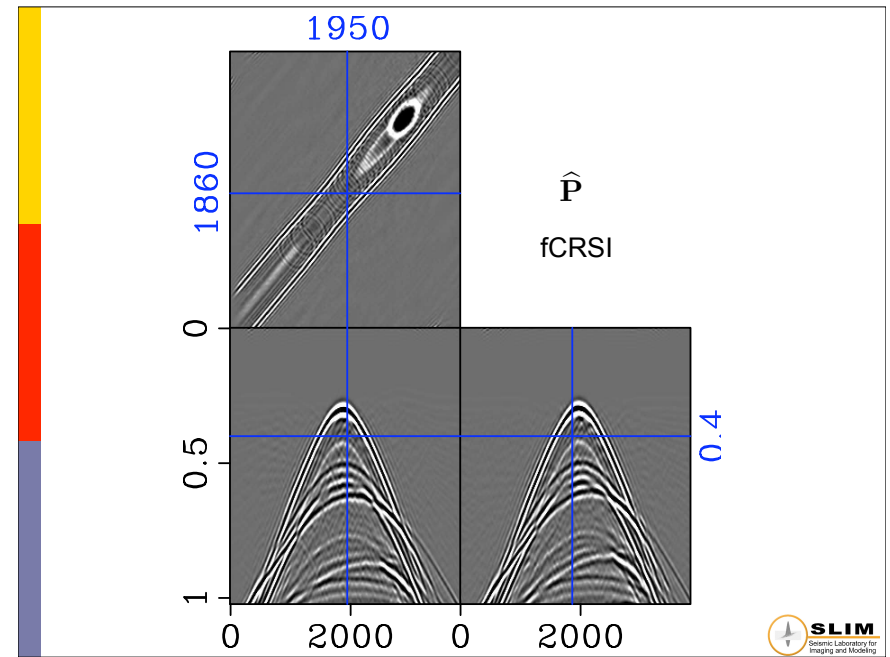
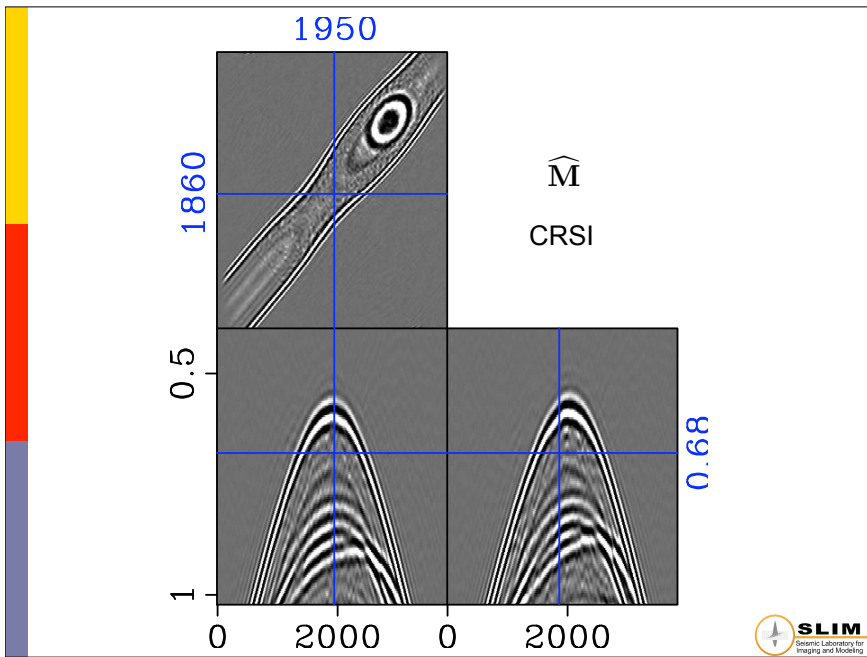
# Nonlinear primary-multiple prediction

joint work with Deli Wang (visitor from Jilin university) and Eric Verschuur



## Multiple prediction with fCRSI





# Curvelet-based Focal transform

Solve

$$\mathbf{P}_\epsilon : \begin{cases} \tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 & \text{s.t. } \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2 \leq \epsilon \\ \tilde{\mathbf{f}} = \mathbf{S}^T \tilde{\mathbf{x}} \end{cases}$$

with

$$\mathbf{A} := \Delta \mathbf{P} \mathbf{C}^T$$

$$\mathbf{S} := \mathbf{C}$$

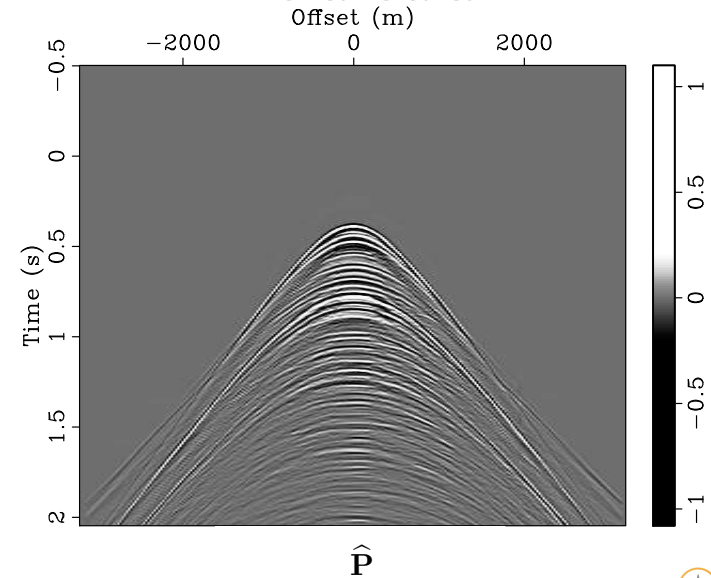
$$\mathbf{y} = \mathbf{P}(\cdot)$$

$$\mathbf{P} = \text{total data}$$

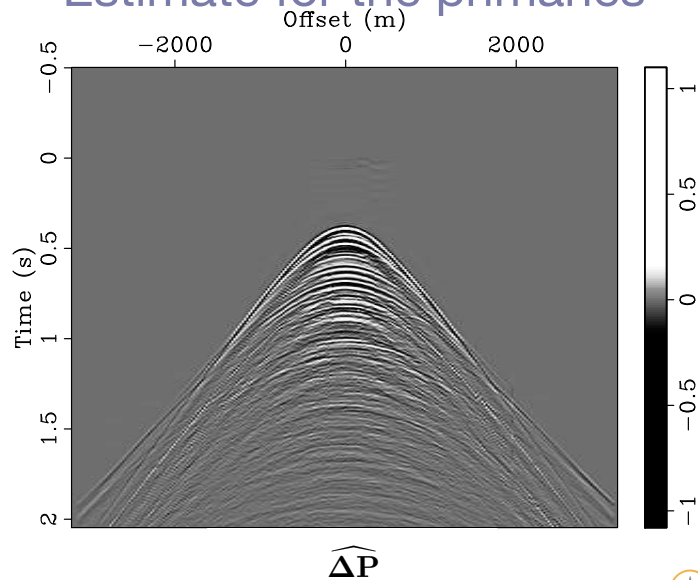
$$\tilde{\mathbf{f}} = \text{focused data.}$$



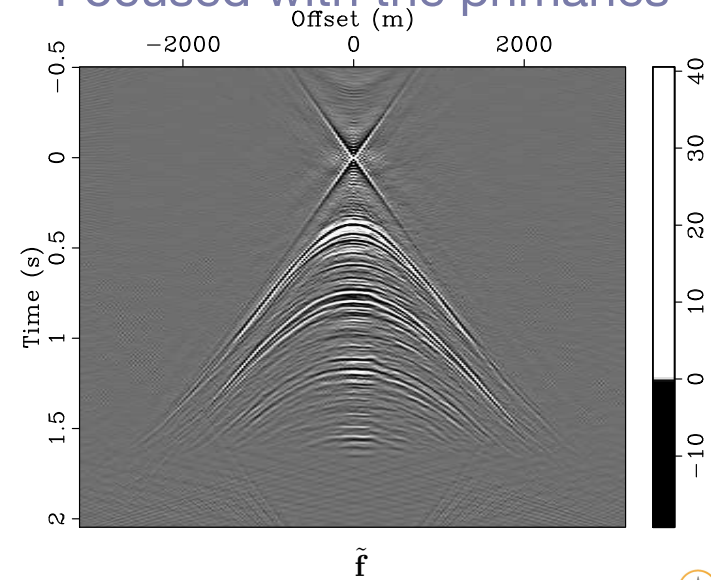
## Total data



## Estimate for the primaries

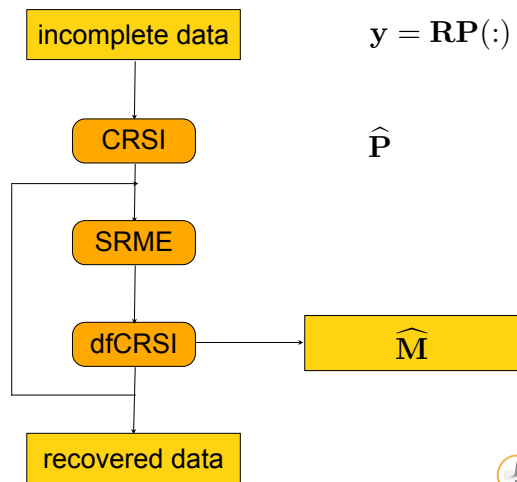


## Focused with the primaries





## Multiple prediction with dfCRSI



## Curvelet-based deFocal transform

Solve

$$\mathbf{P}_\epsilon : \begin{cases} \tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 & \text{s.t. } \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2 \leq \epsilon \\ \tilde{\mathbf{f}} = \mathbf{S}^T \tilde{\mathbf{x}} \end{cases}$$

with

$$\mathbf{A} := \Delta \mathbf{P}^T \mathbf{C}^T$$

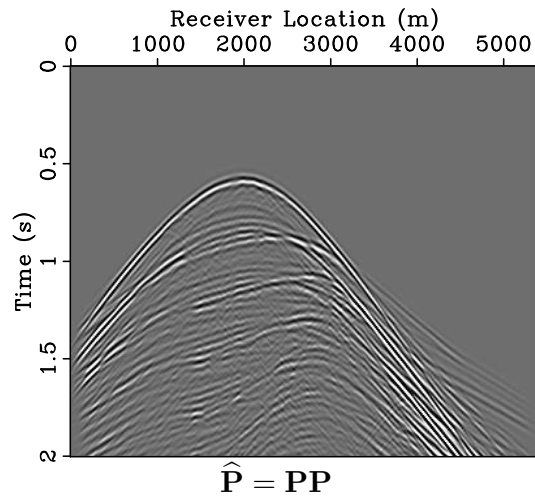
$$\mathbf{S} := \mathbf{C}$$

$$\mathbf{y} = \mathbf{P}(\cdot)$$

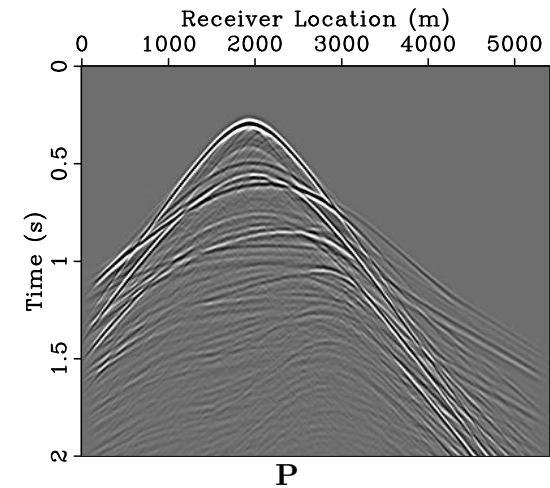
$$\mathbf{P} = \text{total data}$$

$$\tilde{\mathbf{f}} = \text{defocused data.}$$

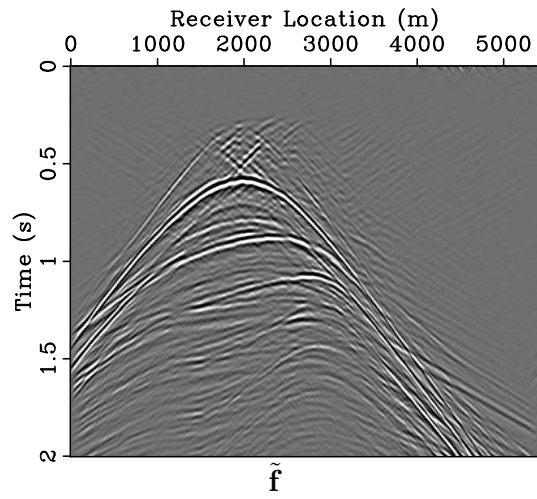
## SRME predicted multiples



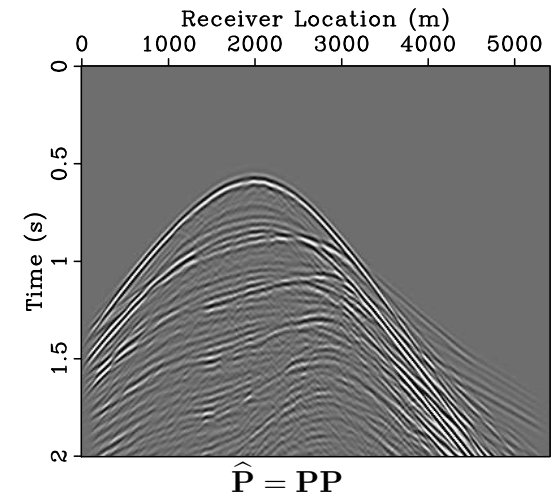
## Original data



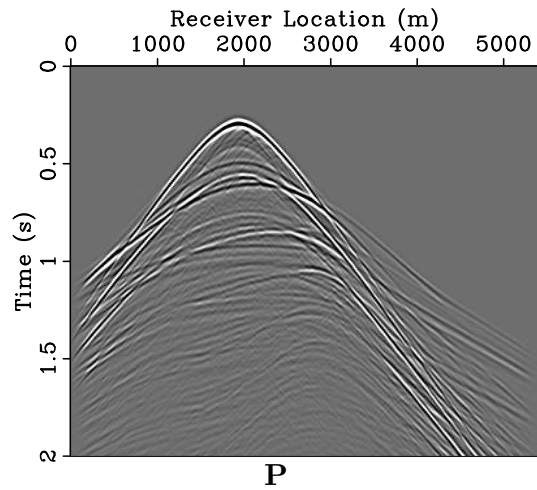
## Multiple estimate by dfCRSI



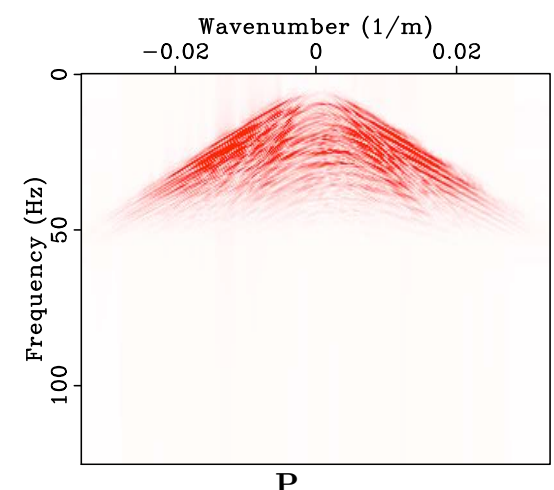
## SRME predicted multiples



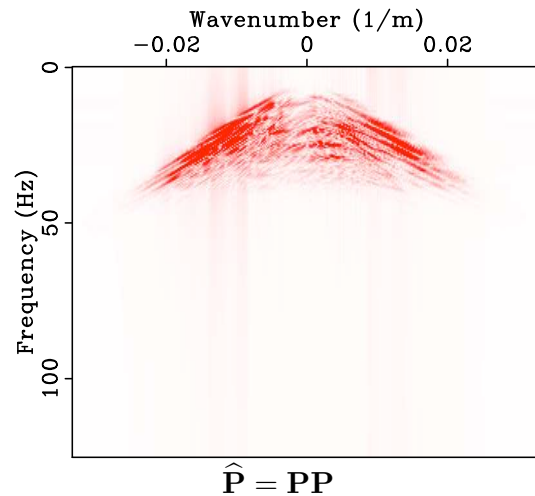
## Original data



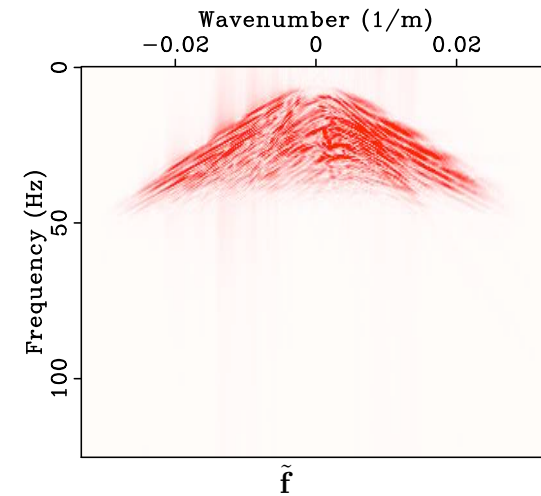
## Original data



## SRME predicted multiples



## Multiple estimate by dfCRSI



## Observations

Daisy-chaining CRSI with fCRSI leads to an improved recovery.

Focused multiples are "deconvolved" w.r.t. source signature and directivity pattern.

Multiple prediction obtained by inverting the "correlation" with the primaries operator

- have a broader frequency band & better amplitudes
- suffer from cross terms due to remnant multiples in the primary operator

## Extensions

part of SINBAD II

# CRSI

Quantitatively determine

- how random is random enough
- acquisition strategies that favor successful recovery
- predictions for accuracy for the recovery error given an acquisitions
- design of acquisition strategies given a desired resolution and recovery accuracy

Impose reciprocity on the recovered matrix

- exploit symmetry relations
- use

$$\mathbf{P} = \frac{1}{2}(\mathbf{P} + \mathbf{P}^T) + \frac{1}{2}(\mathbf{P} - \mathbf{P}^T)$$



# Motivation

Focal transform is like a migration towards the sources.

The same as imaging a point reflector with a directivity pattern.

Use the redundancy in prestack imaged data.

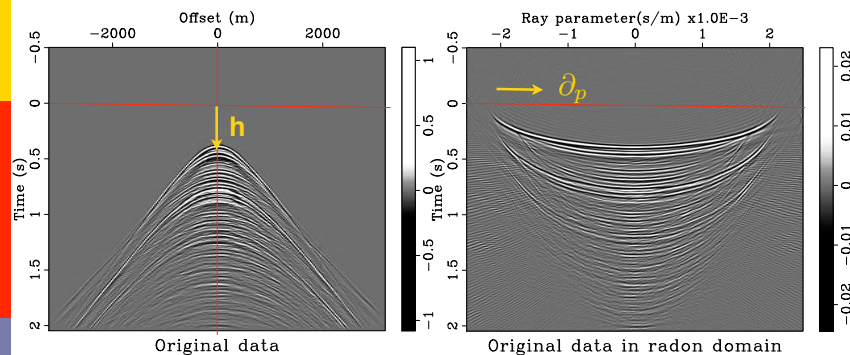
Migration and differential semblance imaging conditions that penalize

- defocusing
- non-smoothness in angle/ray-parameter

**Combine these two focusing in the curvelet domain => multiscale & multidirectional focussing ...**



# Example unfocused

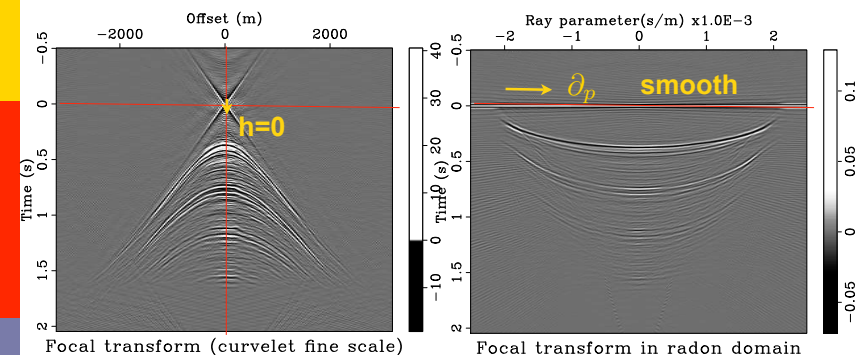


Focusing in phase space

- penalize distance away from focal point (0,0)
- penalize smoothness along line (0,p)



# Example focused



Minimize

$$J_h(\tilde{\mathbf{f}}) = \|\mathbf{h}\tilde{\mathbf{f}}\|_2$$

and

$$J_\theta(\tilde{\mathbf{f}}) = \|\partial_p \tilde{\mathbf{f}}\|_2$$



## Focusing

Curvelet domain is parameterized by  $(x, y, \theta)$ .

Joint focusing in **space** and **angle** can be implemented in the *curvelet* domain.

$$\mathbf{P} : \begin{cases} \tilde{\mathbf{x}} = \min_{\mathbf{x}} \|\mathbf{W}\mathbf{x}\|_1 & \text{subject to } \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2 \leq \epsilon \\ \mathbf{A} := \mathbf{R}\Delta\mathbf{P}\mathbf{C}^T \\ \tilde{\mathbf{f}} = \Delta\mathbf{P}\mathbf{C}^T \tilde{\mathbf{x}} \end{cases}$$

where  $\mathbf{W}$  penalizes **defocusing ...**

Alternative to curvelet domain matched filtering.

Applications

- primary-multiple separation in the focal or inverse data domain (multiples do not focus ...)
- focusing as part of imaging



## Focal transform

- allows for incorporation of a priori information
- leads to an improved recovery

## DeFocal transform

- enhances frequency content of the multiples
- contains Xterms related to remnant multiples

## Focusing

- combined with wavefield extrapolation will enhance the recovery
- will lead to an alternative non-adaptive primary-multiple separation scheme

## Outlook

- Restriction  $\Leftrightarrow$  compression of the operators
- Opens the way to migration-based recovery
- or a more "blue sky" approach of compressive wavefield extrapolation

