

Phase-space matched filtering & migration preconditioning

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Vancouver, February 20-21

Motivation

Migration does not recover the amplitudes.

Least-squares migration is computationally unfeasible.

Lacks robustness w.r.t. noise.

Existing scaling methods

- do not always correct for the order (1 - 2D) of the Hessian (see also Symes '07)
- assume that there are no conflicting dips (conormal)
- do not invert the scaling robustly

Our approach exploits

- invariance of curvelets under the Hessian
- the smoothness of the symbol of the Hessian
- curvelet-domain sparsity

Existing scaling methods

Methods are based on a diagonal approximation of Ψ .

- Illumination-based normalization (Rickett '02)
- Amplitude preserved migration (Plessix & Mulder '04)
- Amplitude corrections (Guitton '04)
- Amplitude scaling (Symes '07)

We are interested in an 'Operator and image adaptive' scaling method which

- estimates the action of Ψ from a reference vector close to the actual image
- assumes a smooth symbol of Ψ in space and angle
- does not require the reflectors to be conormal \Leftrightarrow allows for conflicting dips
- stably inverts the diagonal

Seismic imaging problem



Forward problem

$$F[c]u := \left(\frac{1}{c^2(x)} \cdot \frac{\partial^2}{\partial t^2} - \sum_{i=1}^d \frac{\partial^2}{\partial x_i^2} \right) \mathbf{u}(x, t) = f(x, t)$$

second order hyperbolic PDE

interested in the singularities of

$$m = c - \bar{c}$$

Inverse problem

Minimization:

$$\tilde{m} = \arg \min_m \|d - F[m]\|_2^2$$

After linearization (Born app.) forward model with noise:

$$d(x_s, x_r, t) = (Km)(x_s, x_r, t) + n(x_s, x_r, t)$$

Conventional imaging:

$$(K^T d)(x) = (K^T Km)(x) + (K^T n)(x)$$

$$y(x) = (\Psi m)(x) + e(x)$$

Ψ is prohibitively expensive to invert!

Normal operator

[Stolk 2002, ten Kroode 1997, de Hoop 2000, 2003]

Alternative to expensive least-squares migration.

In high-frequency limit Ψ is a PsDO

$$(\Psi f)(x) = \int_{\mathbb{R}^d} e^{-ix \cdot \xi} a(x, \xi) \hat{f}(\xi) d\xi$$

- pseudolocal
- singularities are preserved
- High-frequency argument

Corresponds to a spatially-varying dip filter after appropriate preconditioning.

Our approach

Formulate as a sparsity- and continuity promoting optimization problem

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

Based on a diagonal approximation

$$\mathbf{A}\mathbf{A}^T \mathbf{r} \simeq \mathbf{\Psi} \mathbf{r} \text{ with } \mathbf{A} = \mathbf{C}^T \mathbf{D}_{\Psi}^{1/2}$$

with \mathbf{r} the reference vector.

Estimate $\mathbf{D}_{\Psi}^{1/2}$ using **smoothness** of the **symbol**.

Diagonal approximation of the Hessian



Existing scaling methods

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- stably inversion of the diagonal

Math

“Precondition” the linearized (Born) modeling operator

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

with

$$\begin{aligned} K &\mapsto K (-\Delta)^{-1/2} & \text{or} & & K &\mapsto \partial_t^{-1/2} K \\ m &\mapsto (-\Delta)^{1/2} m & \text{with} & & ((-\Delta)^\alpha f)^\wedge(\xi) &= |\xi|^{2\alpha} \cdot \hat{f}(\xi). \end{aligned}$$

such that the normal equation is near unitary

$$\begin{aligned} y &= K^T K m \\ &= \Psi m \end{aligned}$$

with $\Psi \approx Id$.

Math cont'd

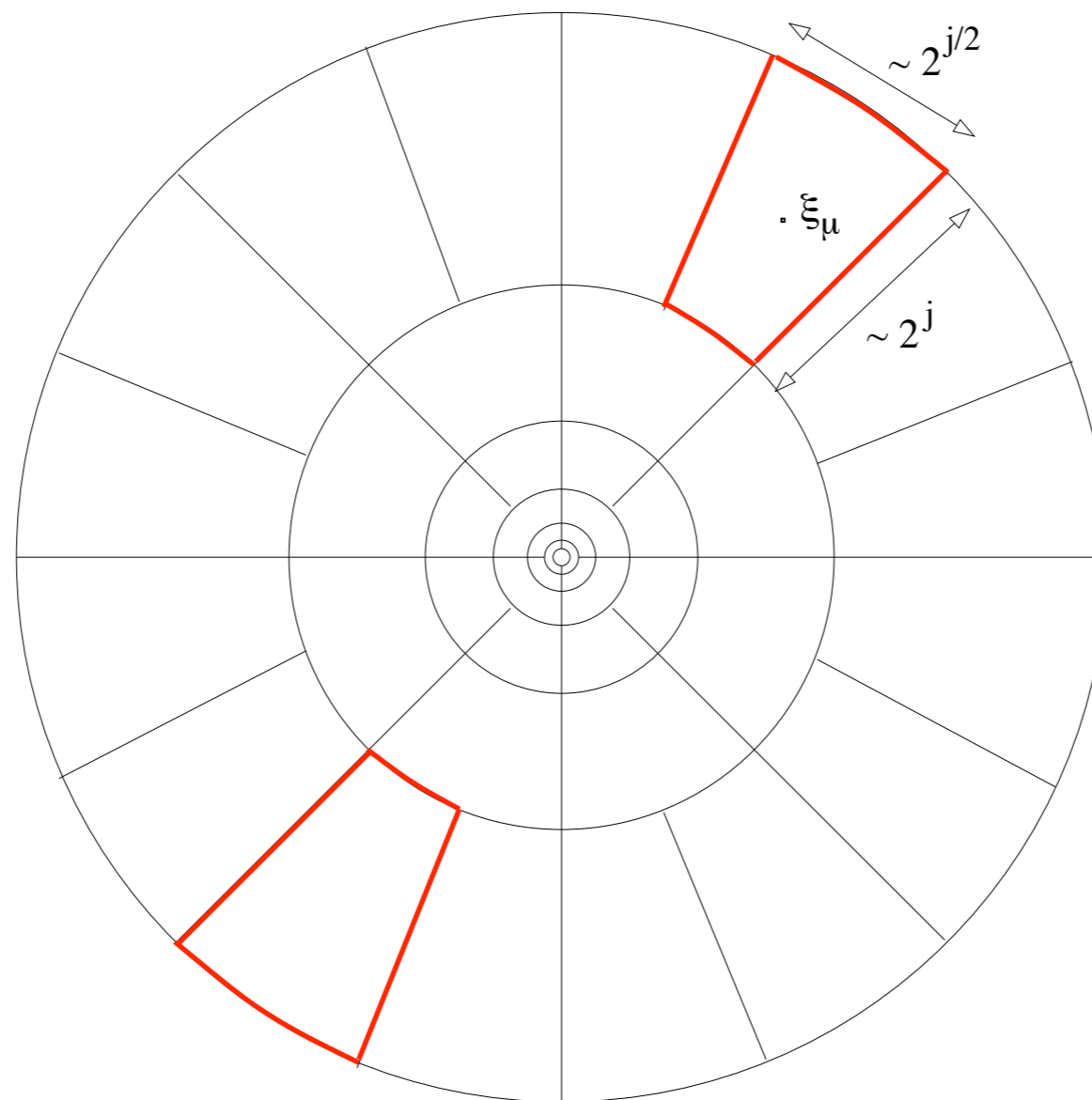
In the high-frequency limit $\Psi = \Psi(x, D)$

- is a pseudodifferential operator of order 0
- has a homogeneous principal symbol $a(x, \xi)$
- acts as a nonstationary dip filter

Lemma 1 *Suppose a is in the symbol class $S_{1,0}^0$, then, with C' some constant, the following holds*

$$\|(\Psi(x, D) - a(x_\nu, \xi_\nu))\varphi_\nu\|_{L^2(\mathbb{R}^n)} \leq C'2^{-|\nu|/2}. \quad (1)$$

Tiling the ξ space



Math cont'd

To approximate Ψ , define the sequence $\mathbf{u} := (u_\mu)_{\mu \in \mathcal{M}} = a(x_\mu, \xi_\mu)$.
Let \mathbf{D}_Ψ be the diagonal matrix with entries given by \mathbf{u} , i.e.,

$$\mathbf{D}_\Psi := \text{diag}(\mathbf{u}).$$

Bound for accuracy of the diagonal approximation

$$\Psi \simeq C^T \mathbf{D}_\Psi C.$$

Theorem 1 *The following estimate for the error holds*

$$\|(\Psi(x, D) - C^T \mathbf{D}_\Psi C)\varphi_\mu\|_{L^2(\mathbb{R}^n)} \leq C'' 2^{-|\mu|/2},$$

where C'' is a constant depending on Ψ .

- accuracy improves for higher frequencies
- amenable for sparsity-promoting inversion

Math cont'd

Allows for an "eigenfunction like" decomposition

$$\begin{aligned}(\Psi \varphi_\mu)(x) &\simeq (C^T \mathbf{D}_\Psi C \varphi_\mu)(x) \\ &= (A A^T \varphi_\mu)(x)\end{aligned}$$

with $A := \sqrt{\mathbf{D}_\Psi} C$ and $A^T := C^T \sqrt{\mathbf{D}_\Psi}$.

Approximation

normal operator

$$\begin{aligned}y(x) &= (\Psi m)(x) + e(x) \\ &\simeq (AA^T m)(x) + e(x) \\ &= Ax_0 + e,\end{aligned}$$

Wavelet-wavelette like

Amenable to nonlinear recovery

Remains to estimate

- scaling coefficients / matched filter coefficients
- use a reference image

Curvelet-domain matched filtering



Matched filtering

Adapt current scaling methodology to phase space.

Exploit smoothness of the symbol valid for smooth velocity models.

Use a reference image sufficiently close to the actual reflectivity.

Generate 'data'

$$\mathbf{b} = \Psi \mathbf{r}$$

with

$$\Psi = \mathbf{K}^T \mathbf{K}$$

\mathbf{K} = discretized linearized Born modeling operator

\mathbf{r} = reference vector

Original formulation

matched filtering

Find '*positive-entry*' **scaling** vector \mathbf{u} such that

$$\mathbf{b} \approx \mathbf{C}^T \mathbf{D}_\Psi \mathbf{C} \mathbf{r} \quad \text{with} \quad \mathbf{D}_\Psi = \text{diag}(\mathbf{u})$$

by solving the *linear* least-squares problem

$$\tilde{\mathbf{u}} = \arg \min_{\mathbf{u}} \frac{1}{2} \|\mathbf{b} - \mathbf{P} \mathbf{u}\|_2^2 + \eta^2 \|\mathbf{L} \mathbf{u}\|_2^2$$

with

$$\mathbf{P} := \mathbf{C}^T \text{diag}(\mathbf{C} \mathbf{r})$$

Original formulation

matched filtering

Impose *smoothness* in phase space

$$\mathbf{L} = [\mathbf{D}_1 \quad \mathbf{D}_2 \quad \mathbf{D}_\theta]$$

Calculate: $\mathbf{b} = \mathbf{\Psi}\mathbf{r}$ and $\mathbf{v} = \mathbf{C}\mathbf{r}$.

Set: $\eta = \eta_{min}$;

while $\exists (\tilde{u}_\mu)_{\mu \in \mathcal{M}} < 0$ **do**

Solve

$$\tilde{\mathbf{u}} = \arg \min_{\mathbf{u}} \frac{1}{2} \|\mathbf{b} - \mathbf{P}\mathbf{u}\|_2^2 + \eta^2 \|\mathbf{L}\mathbf{u}\|_2^2$$

Increase the Lagrange multiplier

$$\lambda = \eta + \Delta\eta$$

end while

Observations

Computation of matched-filter coefficients *expensive*.

- no 'real' positivity *constraint* while
- $\mathbf{K}^T \mathbf{K}$ is a *positive definite* matrix

In addition, our approach does *not* accommodate

- precise phase-space *smoothness*
- *flexibility* to handle *black-box* implementations
- migration operator *preconditioning*
- *incomplete* data
- seismic *source* function

New formulation

matched filtering

Find *positive-entry scaling* vector \mathbf{u} such that

$$\mathbf{b} \approx \mathbf{C}^T \mathbf{D}_\Psi \mathbf{C} \mathbf{r} \quad \text{with} \quad \mathbf{D}_\Psi = \text{diag}(\mathbf{u})$$

Translates into minimizing

$$J_\gamma(\mathbf{z}) = \frac{1}{2} \|\mathbf{d} - \mathbf{F}_\gamma \exp(\mathbf{z})\|_2^2 \quad \text{with} \quad \tilde{\mathbf{u}} = \exp(\tilde{\mathbf{z}})$$

involving the following system of equations

$$\begin{bmatrix} \mathbf{b} \\ \mathbf{0} \end{bmatrix} = \begin{bmatrix} \mathbf{C}^T \text{diag}\{\mathbf{C} \mathbf{r}\} \\ \gamma \mathbf{L} \end{bmatrix} \mathbf{w} \quad \text{or} \quad \mathbf{d} = \mathbf{F}_\gamma \mathbf{w}$$

with the gradient

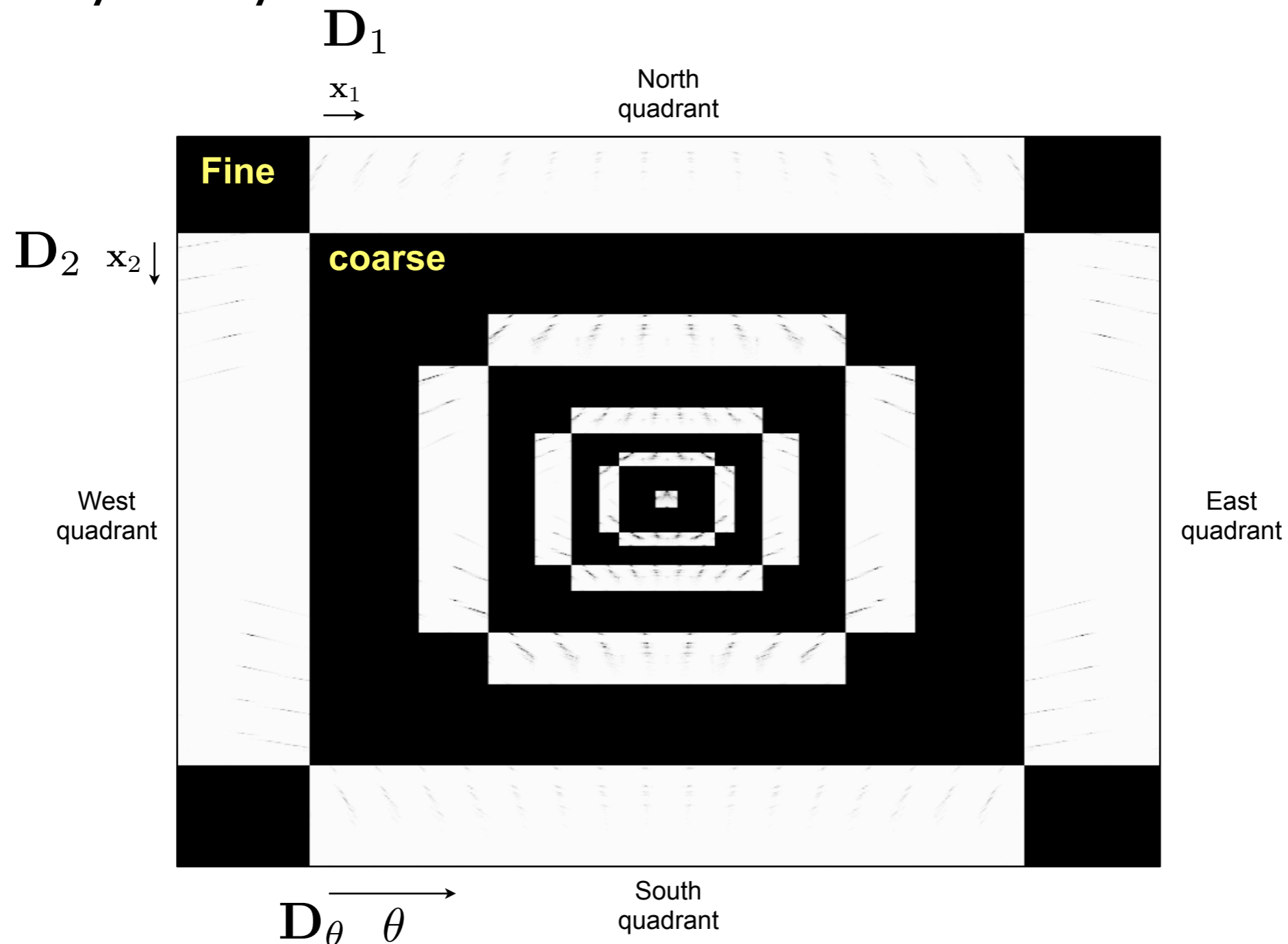
$$\text{grad} J(\mathbf{z}) = \text{diag}\{e^{\mathbf{z}}\} [\mathbf{F}^T (\mathbf{F} e^{\mathbf{z}} - \mathbf{d})]$$

Matched filtering

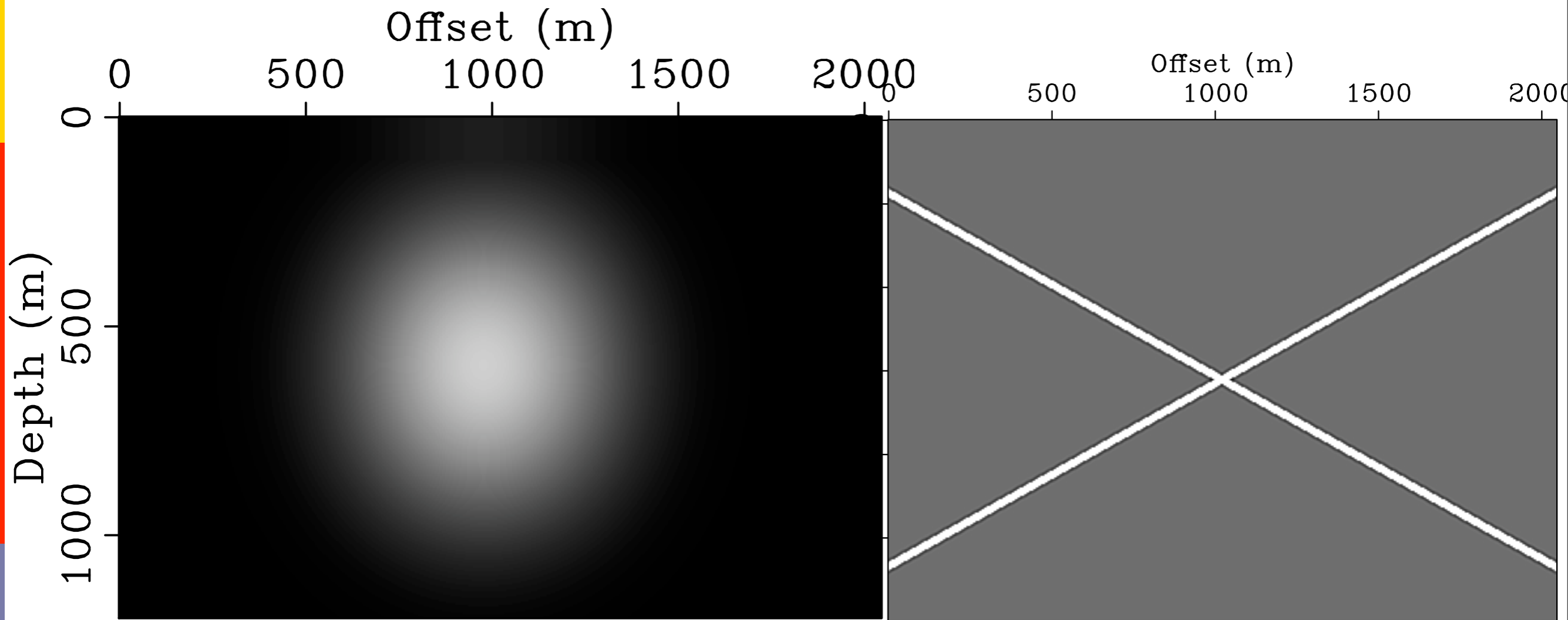
Impose smoothness in phase space through

$$\mathbf{L} = \left[\mathbf{D}_1^T \quad \mathbf{D}_2^T \quad \mathbf{D}_\theta^T \right]^T$$

Positivity of symbol is assured.

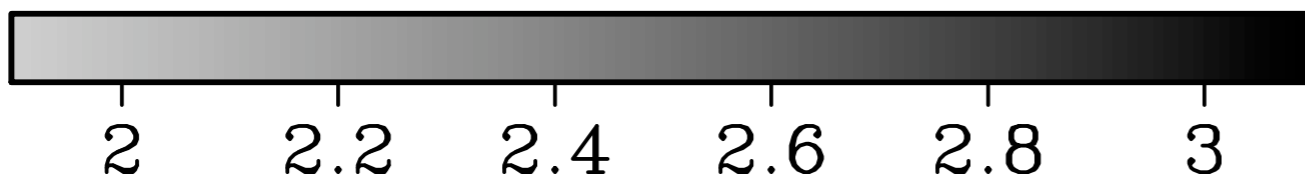


Example

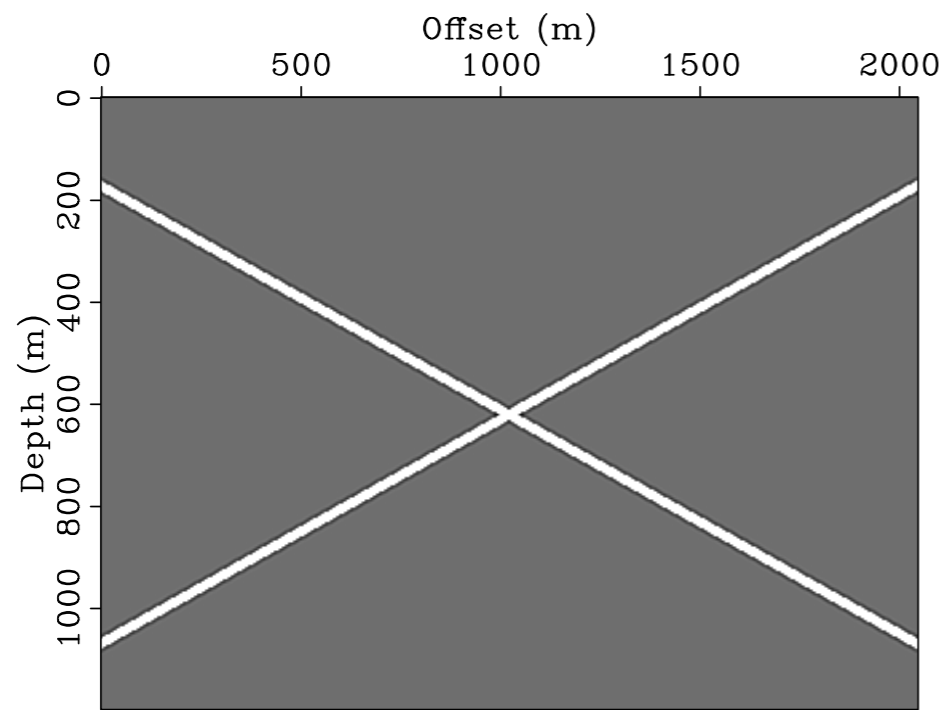


Lens Velocity Model

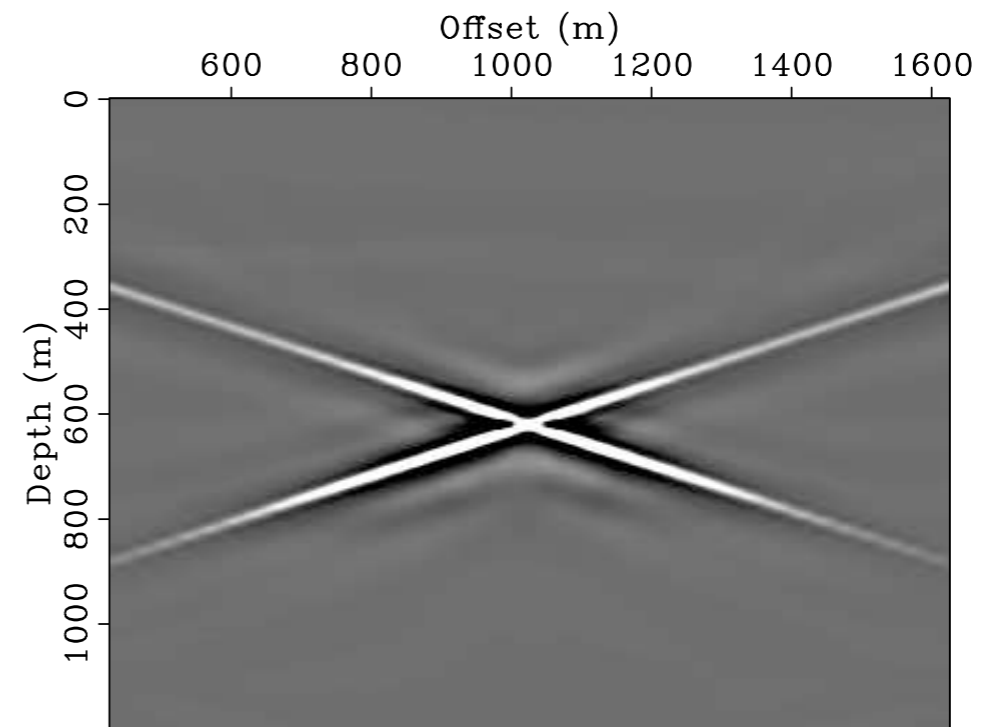
Reflectivity



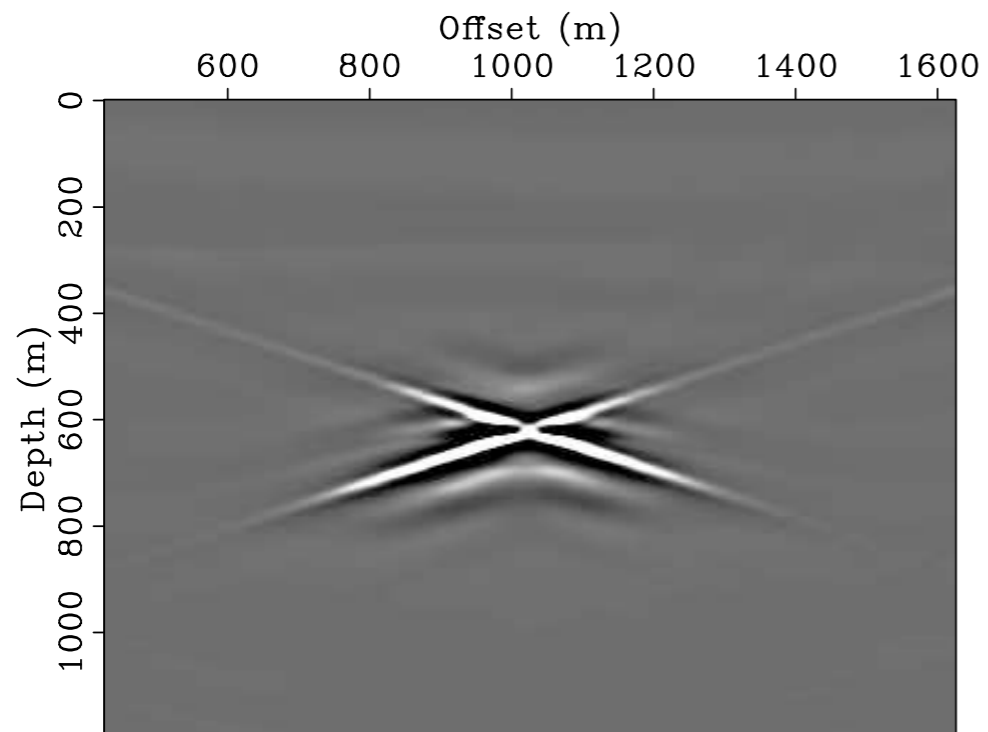
Example



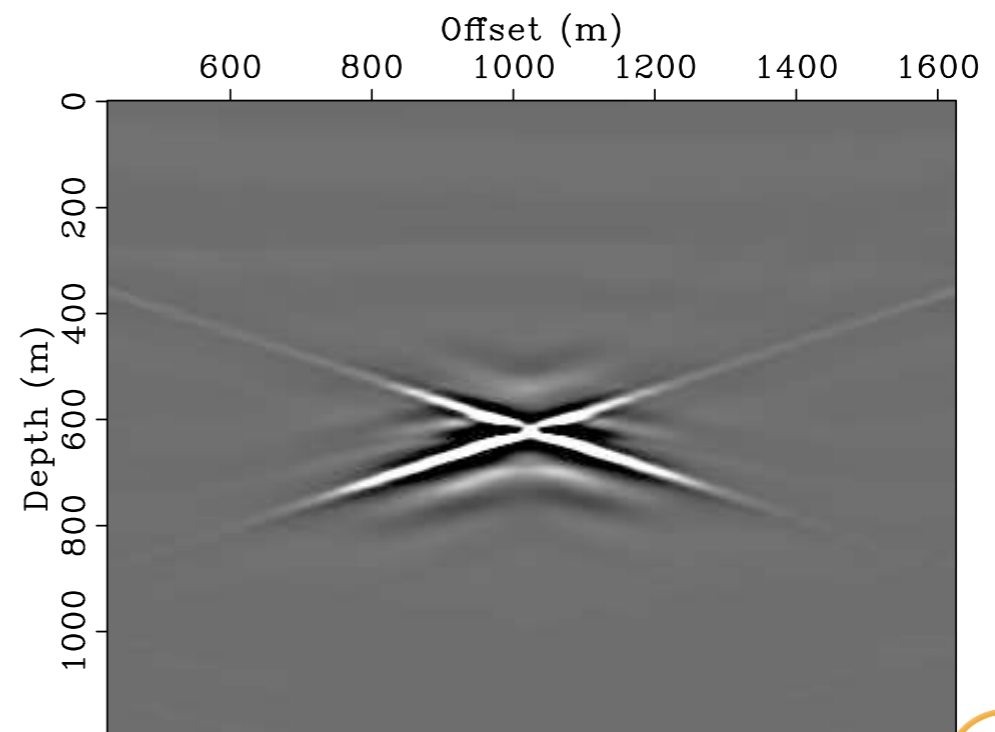
Reflectivity



Migrated Image

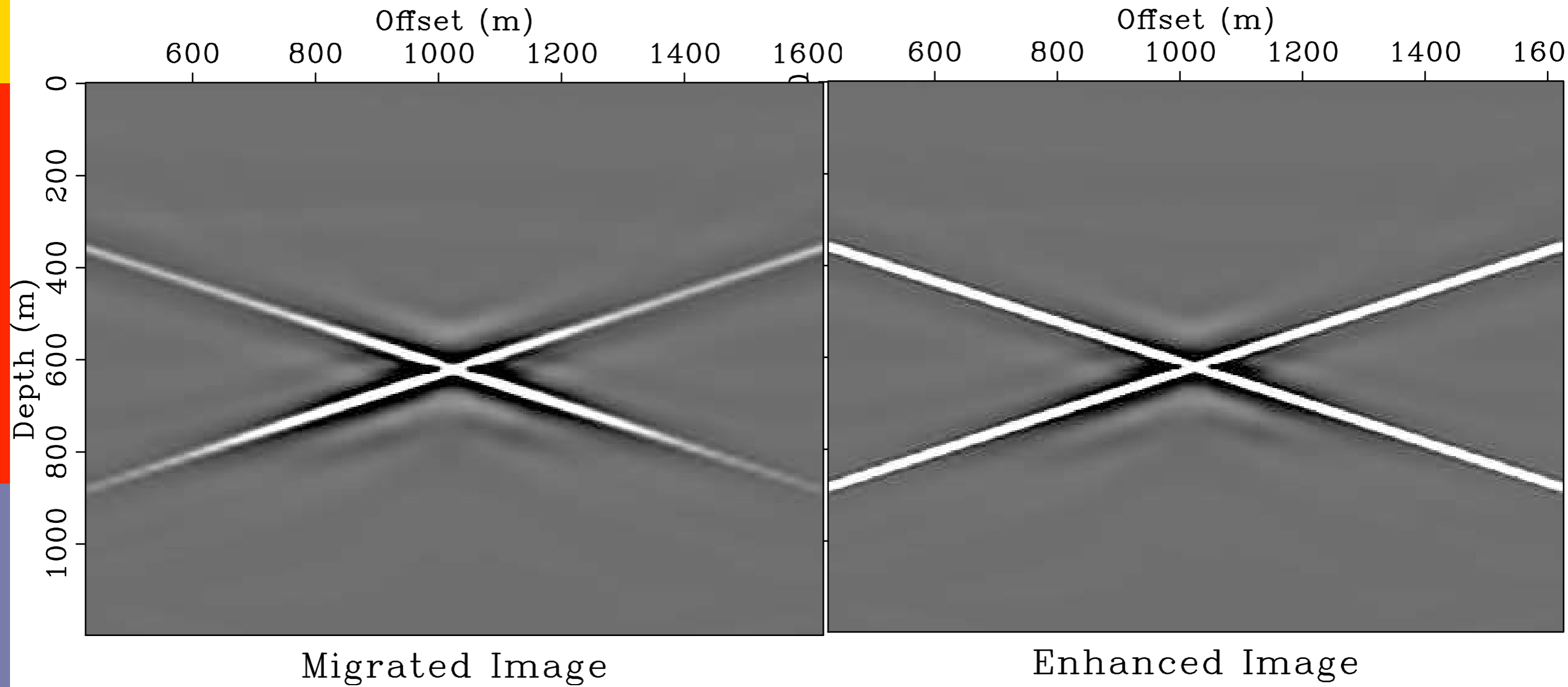


Remigrated



Approximate Remigrated

Example



Matched filtering

new parameterization

Problems:

- computation of the matched-filter coefficients expensive (# of unknowns = length of curvelet vector)
- Limited smoothness

Parameterize phase space (x, y, θ)

- introduce low-dimensional parameterization phase space
- use B-splines
- define the scaling vector in terms of a spline synthesis

$$\mathbf{u} = \mathbf{B}\boldsymbol{\alpha}$$

with for each scale

$$\mathbf{B} = [\mathbf{B}_1 \quad \mathbf{B}_2 \quad \mathbf{B}_\theta]$$

Matched filtering

new parameterization

Find *positive-entry* scaling vector \mathbf{u} such that

$$\mathbf{b} \approx \mathbf{C}^T \mathbf{D}_\Psi \mathbf{C} \mathbf{r} \quad \text{with} \quad \mathbf{D}_\Psi = \text{diag}(\mathbf{u})$$

Minimize

$$J_\gamma(\boldsymbol{\alpha}) = \frac{1}{2} \|\mathbf{b} - \mathbf{F} \exp(\mathbf{B}\boldsymbol{\alpha})\|_2^2 + \frac{1}{2} \gamma \|\boldsymbol{\alpha}\|_2^2$$

■ with

$$\mathbf{F} = \mathbf{C}^H \text{diag}(\mathbf{C} \mathbf{r}) \quad \text{and} \quad \tilde{\mathbf{u}} = \exp(\mathbf{B}\boldsymbol{\alpha})$$

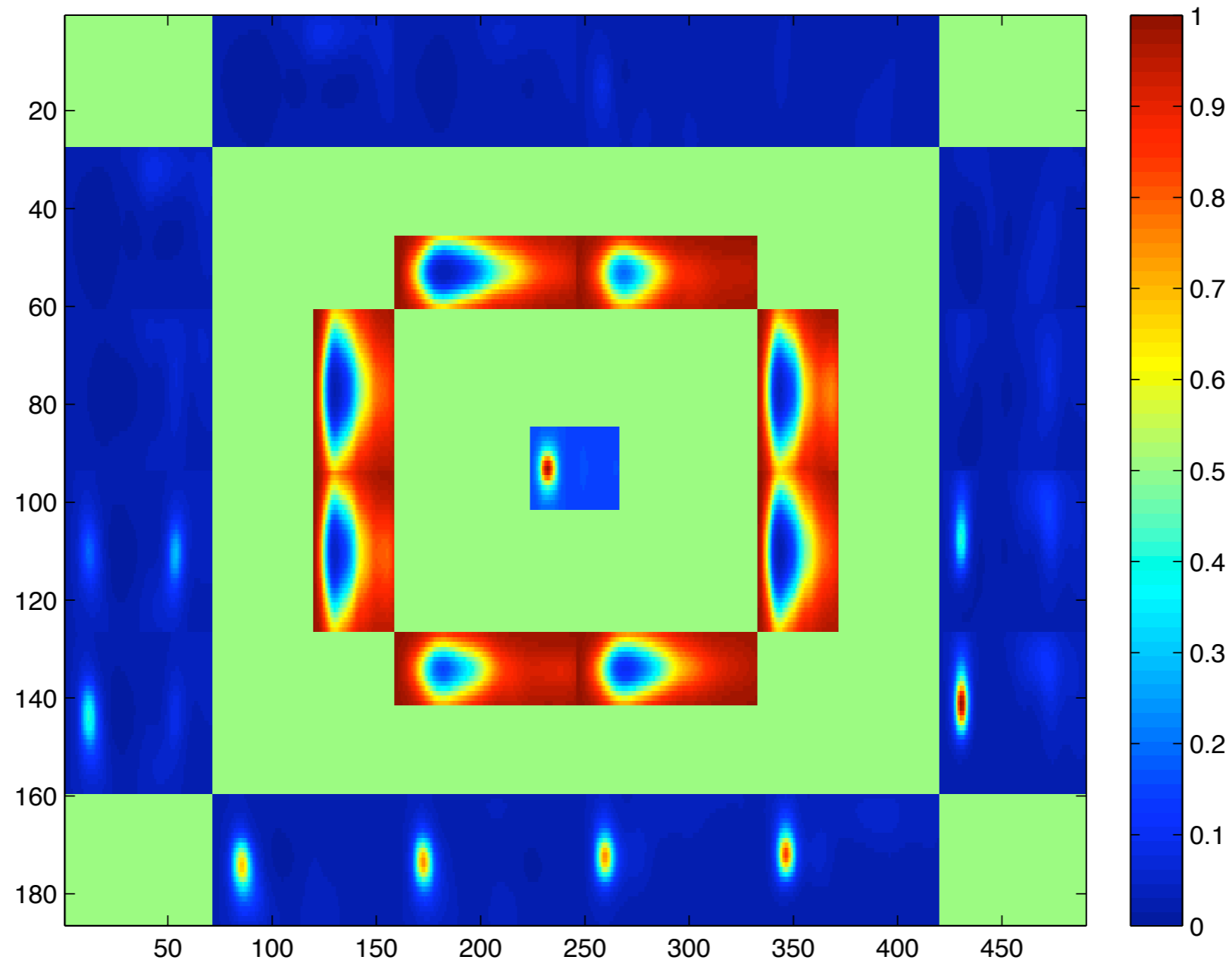
■ assures positivity (Vogel '02)

■ smoothness depends on # of splines and regularization

With the gradient (Vogel '02)

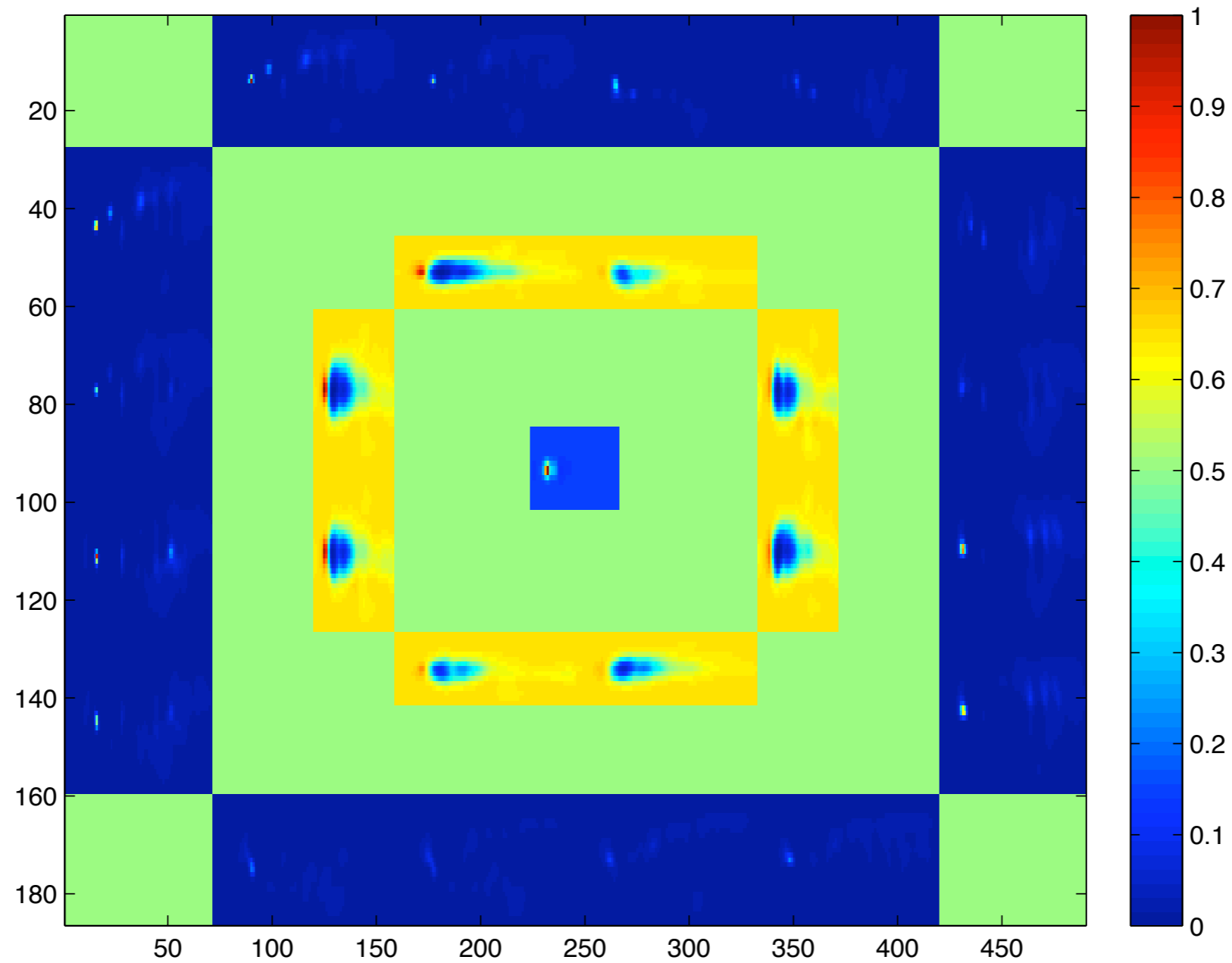
$$\text{grad} J(\boldsymbol{\alpha}) = \text{diag}\{\exp(\mathbf{B}\boldsymbol{\alpha})\} [(\mathbf{F}^T \mathbf{F} + \gamma \mathbf{I}) \exp(\mathbf{B}\boldsymbol{\alpha}) - \mathbf{F}^T \mathbf{b}]$$

Spline



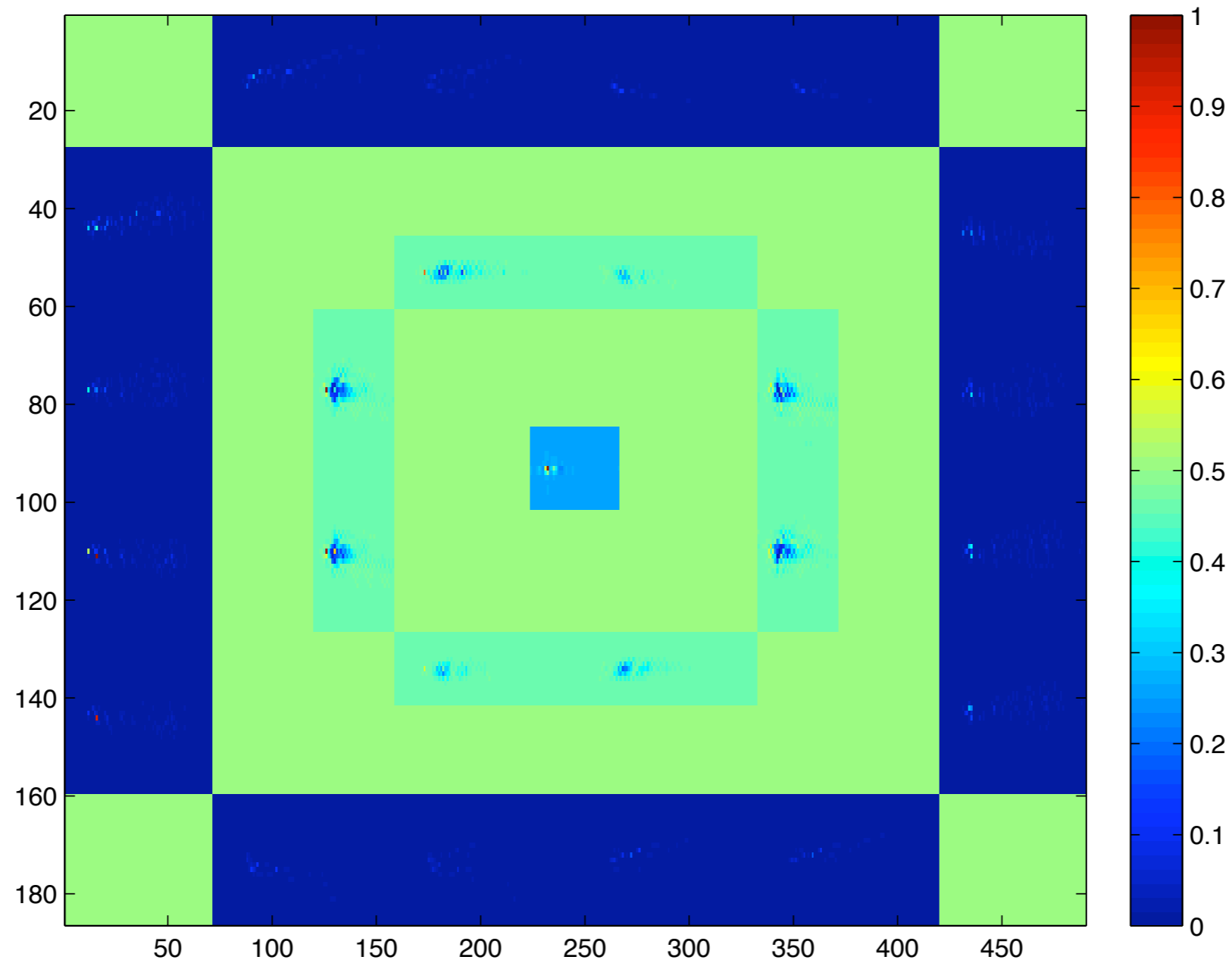
Lambda=0 perc=1%

Spline



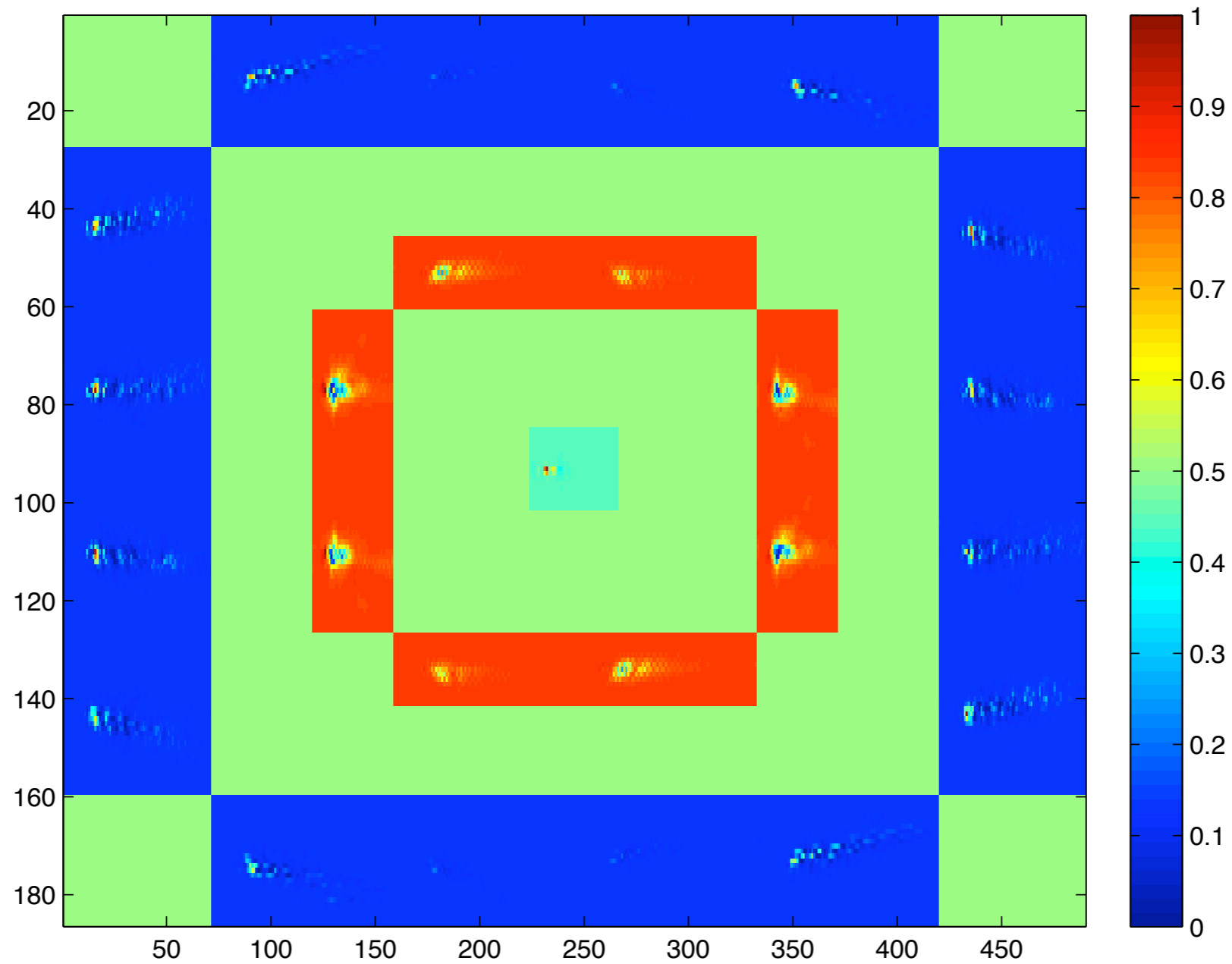
Lambda=0 perc=3%

Spline



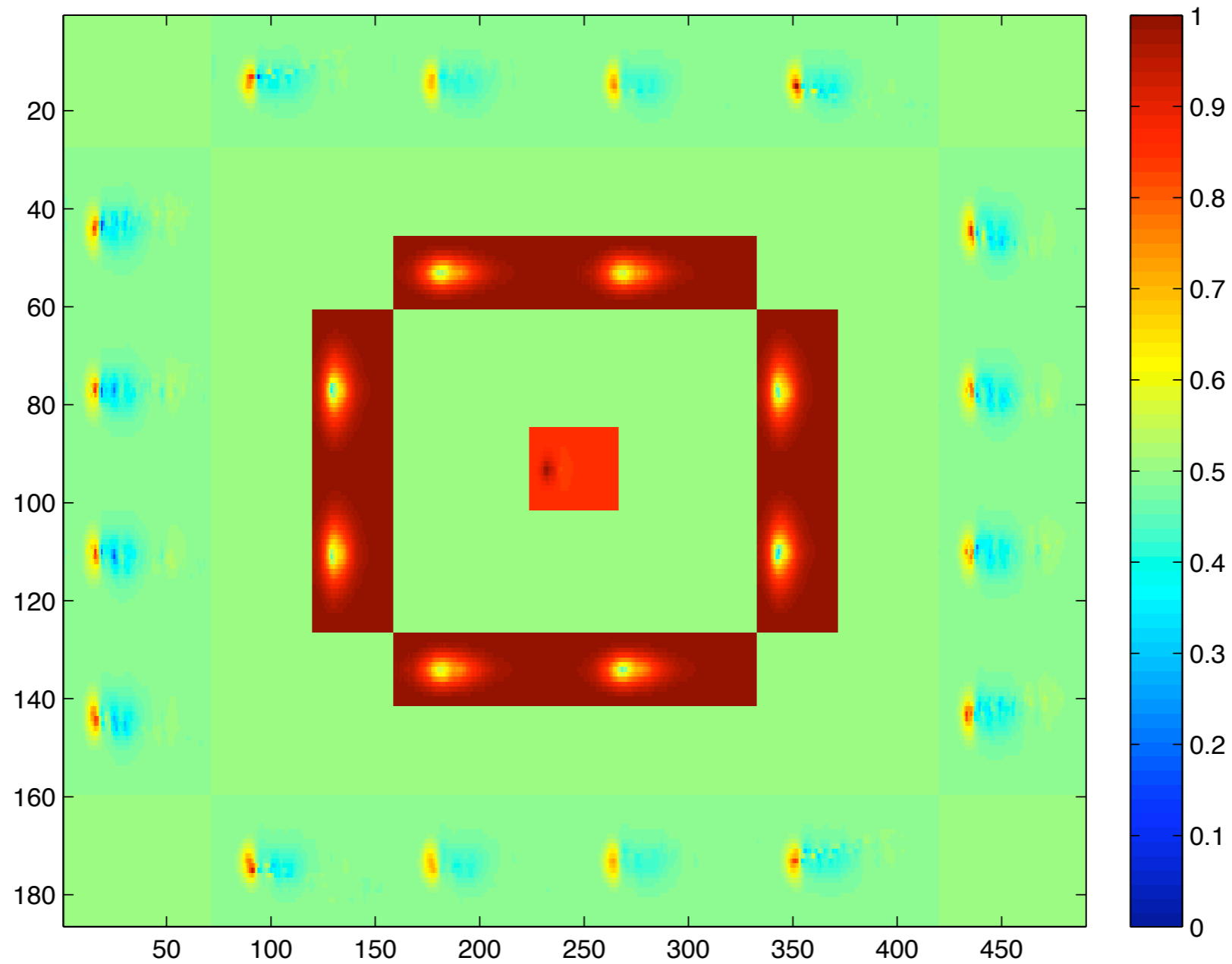
Lambda=0 perc=30%

No spline



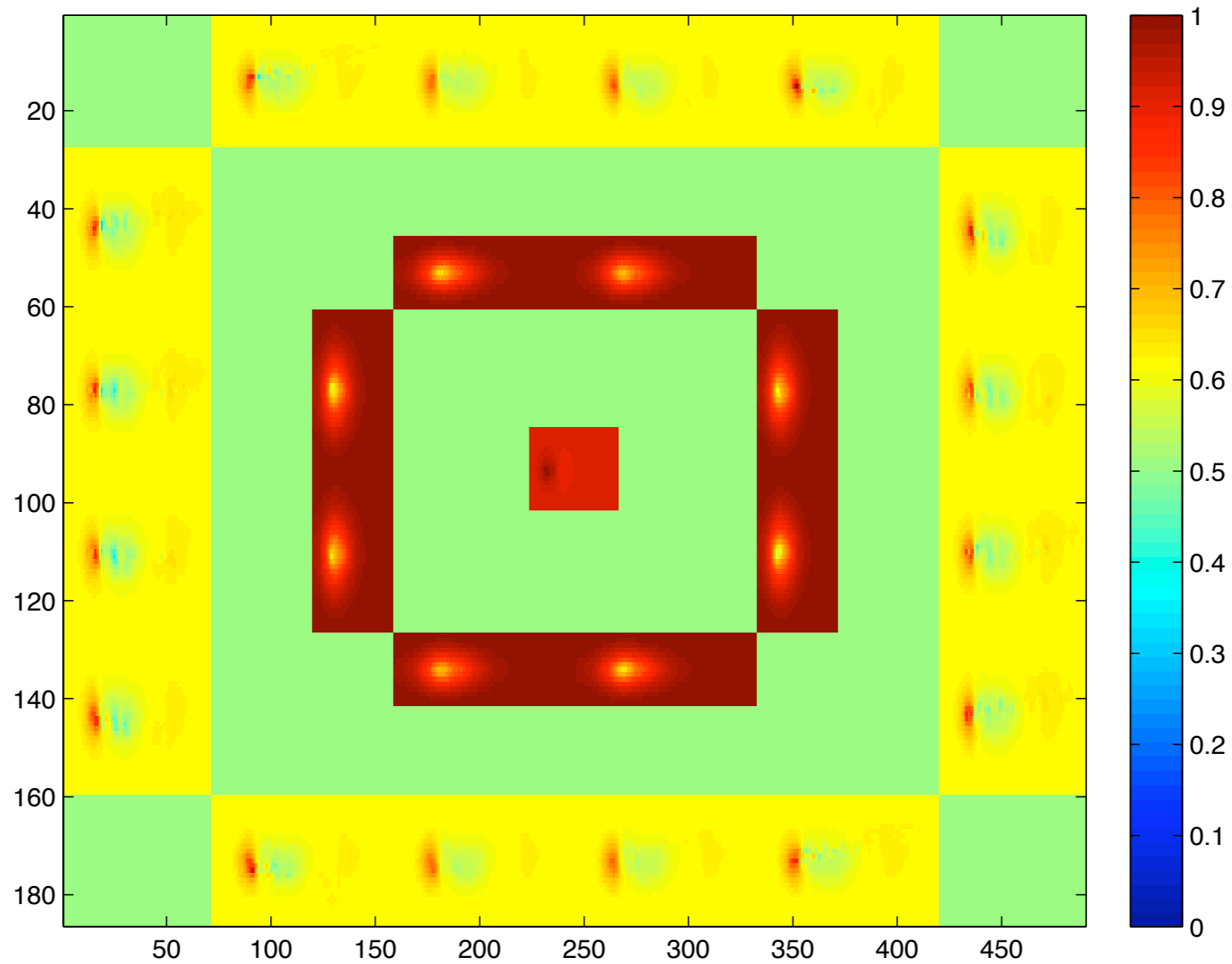
Lambda=0.01

No spline



Lambda=0.05

No spline



Lambda=0.07

Observations

Precise smoothness control

- # of nodes
- size of the regularization parameter

Dimensionality reduction should lead to faster convergence.

More work to study the performance.

Extensions



Black-box utility

Approach relied on zero-order operator.

- known when operators are understood exactly
- corrected for in the “migration operator” wavelet

Introduce additional matched filter by ‘generating data’

$$\mathbf{f} = \mathbf{K}\mathbf{K}^T \mathbf{d}$$

and minimize

$$J_\eta(\mathbf{z}) = \frac{1}{2} \|\mathbf{f} - \mathcal{F}^H \text{diag}(\mathcal{F}\mathbf{d}) \exp(2\mathbf{z})\|_2^2 + \frac{1}{2} \eta \|\mathbf{L}\mathbf{z}\|_2^2$$

Redefine

$$\mathbf{K} \mapsto \mathcal{F}^H \text{diag}(\tilde{\mathbf{h}}) \mathcal{F}\mathbf{K} \quad \text{and} \quad \tilde{\mathbf{h}} = \exp(\tilde{\mathbf{z}})$$

or equivalently replace the source function

$$\phi \mapsto \mathcal{F}^H \text{diag}(\tilde{\mathbf{h}}) \mathcal{F}\phi$$

Migration preconditioning

Forward model:

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

Ideal right preconditioning

$$\mathbf{K} \mapsto \mathbf{K}(\mathbf{K}^T \mathbf{K})^{-1/2}$$

$$\mathbf{m} \mapsto (\mathbf{K}^T \mathbf{K})^{1/2} \mathbf{m}$$

yielding

$$\mathbf{K}^T \mathbf{K} = \mathbf{I}$$

Migration preconditioning

Approximate with curvelet preconditioning.

Define

$$\mathbf{A} := \mathbf{K} \mathbf{C}^T \mathbf{D}_{\Psi}^{-\frac{1}{2}}$$
$$\mathbf{x} := \mathbf{D}_{\Psi}^{\frac{1}{2}} \mathbf{C} \mathbf{m}$$

Such that

$$\mathbf{A}^T \mathbf{A} \approx \mathbf{I}$$

by virtue of

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

- calculate the diagonal approximation from reference vector and demigrated-migrated reference vector
- estimate the inverse square root directly

Migration preconditioning

Minimize

$$J_\gamma(\boldsymbol{\alpha}) = \frac{1}{2} \|\mathbf{r} - \mathbf{F} \exp(2 \cdot \mathbf{B}\boldsymbol{\alpha})\|_2^2 + \frac{1}{2} \gamma \|\boldsymbol{\alpha}\|_2^2$$

with

$$\mathbf{F} = \mathbf{C}^H \text{diag}(\mathbf{C}\mathbf{b}) \text{ and } \tilde{\mathbf{u}} = \exp(\mathbf{B}\boldsymbol{\alpha})$$

yielding

$$\mathbf{D}_\psi^{-\frac{1}{2}} = \text{diag}(\tilde{\mathbf{u}})$$

Seismic data recovery

Migration operator is expensive but the ultimate interpolator.

Solve

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

- recovery of data and image from incomplete data
- compression of the operator (e.g. subset of shots or temporal frequencies)
- migration will enhance the recovery
 - increased incoherence
 - additional focusing

Conclusions & future plans

Low-dimensional spline offers more control

Formulation remains to be tested

- for migration-amplitude recovery
- primary-multiple separation

Extensions

- will be reported on during next meeting

Migration based wavefield recovery seems natural but is not the only choice.

Acknowledgments

SLIM team: Gilles Hennenfent, Sean Ross Ross, Cody Brown, Henryk Modzelewski for SLIMpy
Eric Verschuur, input in primary-multiple separation
Chris Stolk for his input in phase space regularization
E. J. Candès, L. Demanet, D. L. Donoho, and L. Ying for CurveLab

S. Fomel, P. Sava, and other developers of Madagascar

This presentation was carried out as part of the SINBAD project with financial support, secured through ITF, from the following organizations: BG, BP, Chevron, ExxonMobil, and Shell. SINBAD is part of the collaborative research & development (CRD) grant number 334810-05 funded by the Natural Science and Engineering Research Council (NSERC).