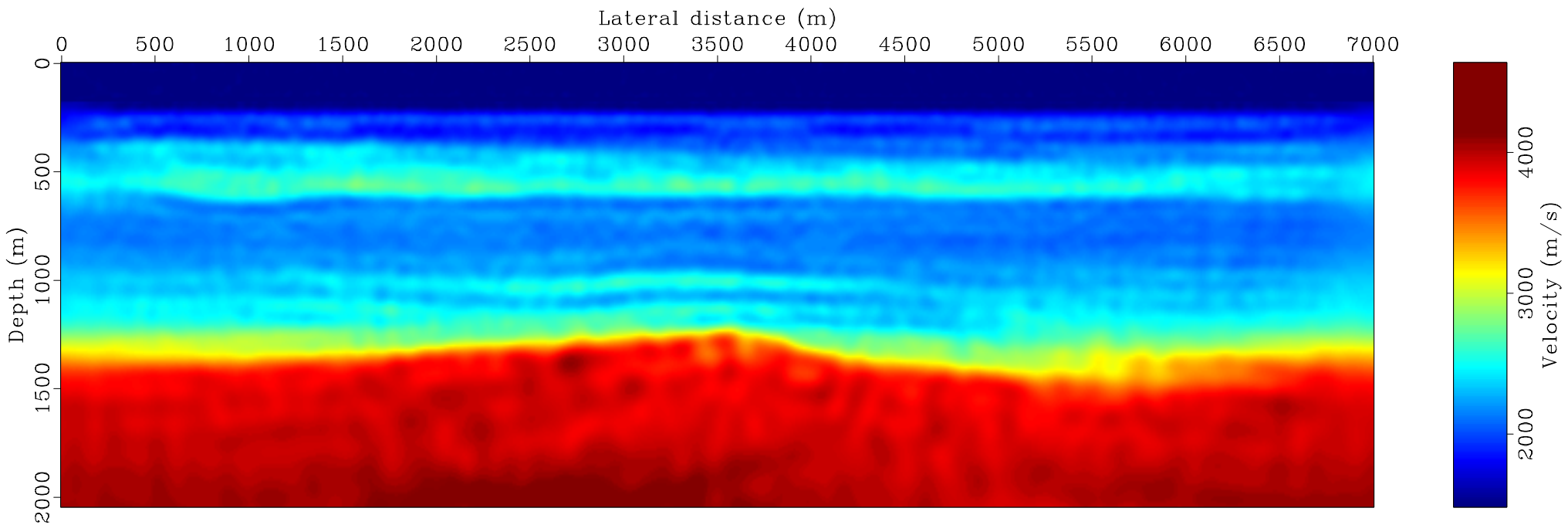




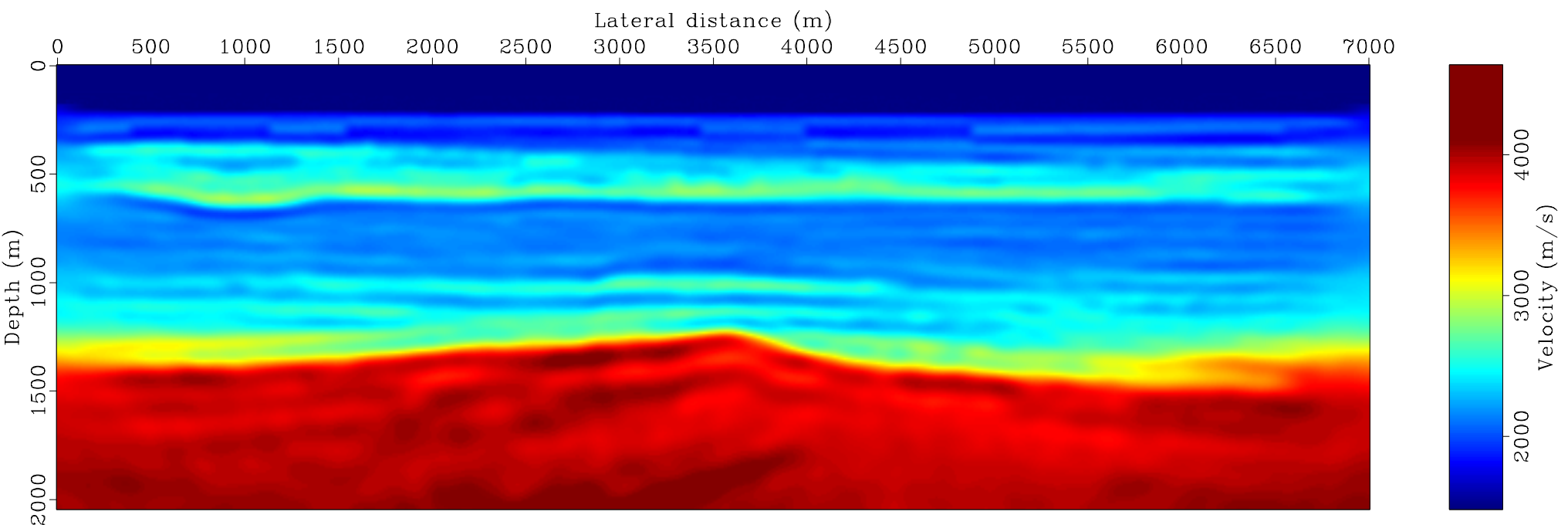
Sparsity-promoting migration accelerated by message passing

Xiang Li and Felix J. Herrmann

Motivation

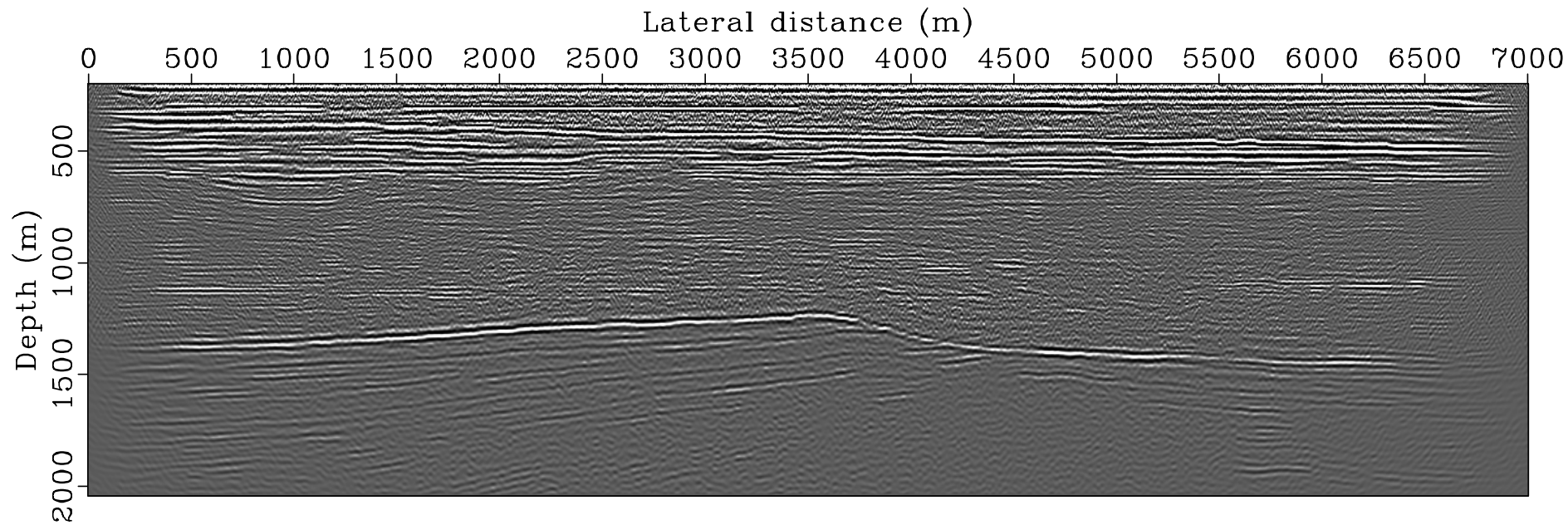


standard GN
FWI

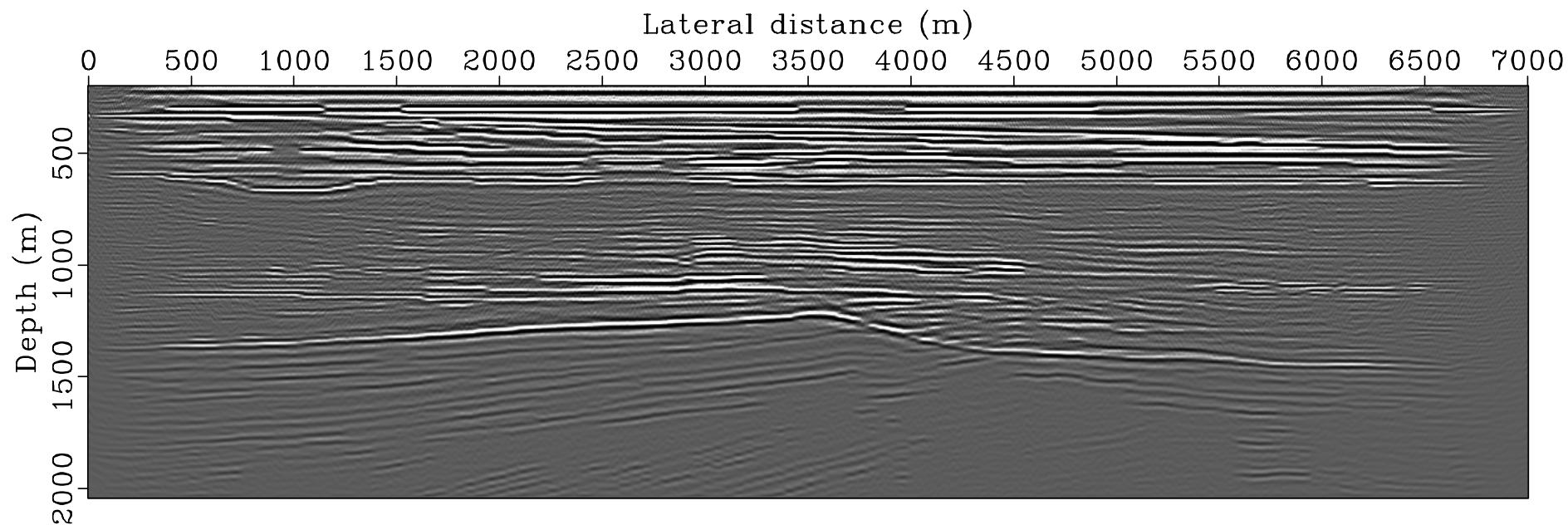


sparsity-
promoting
GN FWI

Motivation



standard
least-squares
migration



sparsity
promoting
least-squares
migration

Outline

- sparsity promoting Gauss-Newton FWI to generate initial model
- sparsity-promoting imaging for migration

Making sparsity-promoting imaging computationally feasible...

Full-waveform inversion

Full waveform inversion

$$\underset{\mathbf{m}, \alpha}{\text{minimize}} \frac{1}{2} \|\mathbf{D} - \alpha \mathcal{F}[\mathbf{m}]\|_F^2$$

$\mathbf{D}$: observed data

$\mathcal{F}$: forward modelling kernel

α : source wavelet

$\mathbf{m}$: model parameters

Gauss-Newton

Gauss-Newton subproblem:

$$\underset{\delta \mathbf{m}}{\text{minimize}} \frac{1}{2} \left\| \underbrace{\mathbf{D} - \alpha \mathcal{F}(\mathbf{m})}_{\mathbf{b}} - \underbrace{\alpha \nabla \mathcal{F}(\mathbf{m})}_{\mathbf{A}} \underbrace{\delta \mathbf{m}}_{\mathbf{x}} \right\|_F^2$$

- least-squares inversion problem
- no explicit Jacobian required

Sparsity-promoting GN

Gauss-Newton subproblem:

$$\underset{\delta \mathbf{m}}{\text{minimize}} \quad \frac{1}{2} \|\mathbf{D} - \alpha \mathcal{F}(\mathbf{m}) - \alpha \nabla \mathcal{F}(\mathbf{m}) \mathbf{C}^T \delta \mathbf{x}\|_F^2 \quad \text{s.t.} \quad \|\delta \mathbf{x}\|_1 < \tau$$
$$\delta \mathbf{m} = \mathbf{C}^T \delta \mathbf{x}$$

- suppress incoherent noise/artifacts by one-norm constraint in a transform domain
- randomized subsets of shots to reduce computational costs

[Pratt, '98]

Source estimation

Source estimation at the k^{th} iteration:

$$\alpha_k = \arg \min_{\alpha} \|\mathbf{D}_k - \alpha \mathcal{F}(\mathbf{m}_k)\|_F^2$$

- ▶ source estimation handles amplitude problems
- ▶ cheap to evaluate

Sparsity-promoting GN FWI

Algorithm 1: Sparsity-promoting Gauss-Newton FWI

Result: Output estimate for the model $\mathbf{m}$

```

 $\mathbf{m} \leftarrow \mathbf{m}_0; k \leftarrow 0;$                                      // initial model
while not converged do
     $\alpha_k \leftarrow \arg \min_{\alpha} \|\mathbf{D}_k - \alpha \mathcal{F}(\mathbf{m}_k)\|_F^2;$            // source estimation
     $\delta \mathbf{D}_k \leftarrow \mathbf{D}_k - \alpha_k \mathcal{F}(\mathbf{m}_k);$                          // wavefield residual
     $\delta \mathbf{x}_k \leftarrow \arg \min_{\delta \mathbf{x}} \frac{1}{2} \|\delta \mathbf{D}_k - \alpha \nabla \mathcal{F}(\mathbf{m}_k) \mathbf{C}^T \delta \mathbf{x}\|_2^2$  s.t.  $\|\delta \mathbf{x}\|_1 \leq \tau_k$ 
     $\mathbf{m}^{k+1} \leftarrow \mathbf{m}^k + \mathbf{C}^T \delta \mathbf{x};$                                // update model
     $k \leftarrow k + 1;$ 
end
  
```

Examples

Acquisition topology:

- 350 shots with interval 20 m
- 701 receivers with interval 10 m

Observed data is generated by

- time domain finite difference modeling method with PML boundary
- 12 Hz Ricker wavelet

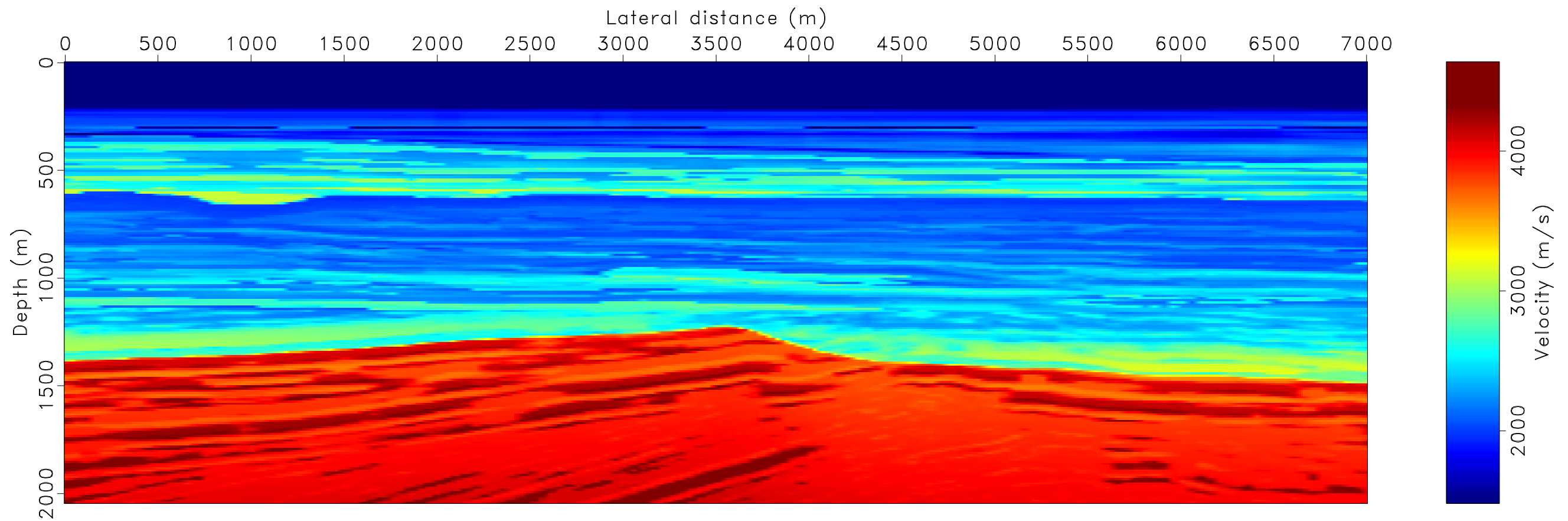
Examples

Inversion parameters:

- 10 frequency bands for 3-12 Hz.
- each band contain 4 frequencies
- inversion using frequency modeling kernel (Helmholtz)
- grid size is determined by minimal wavelength
- solve 5-10 GN subproblems for each frequency band
- < 20 iterations for each GN subproblem

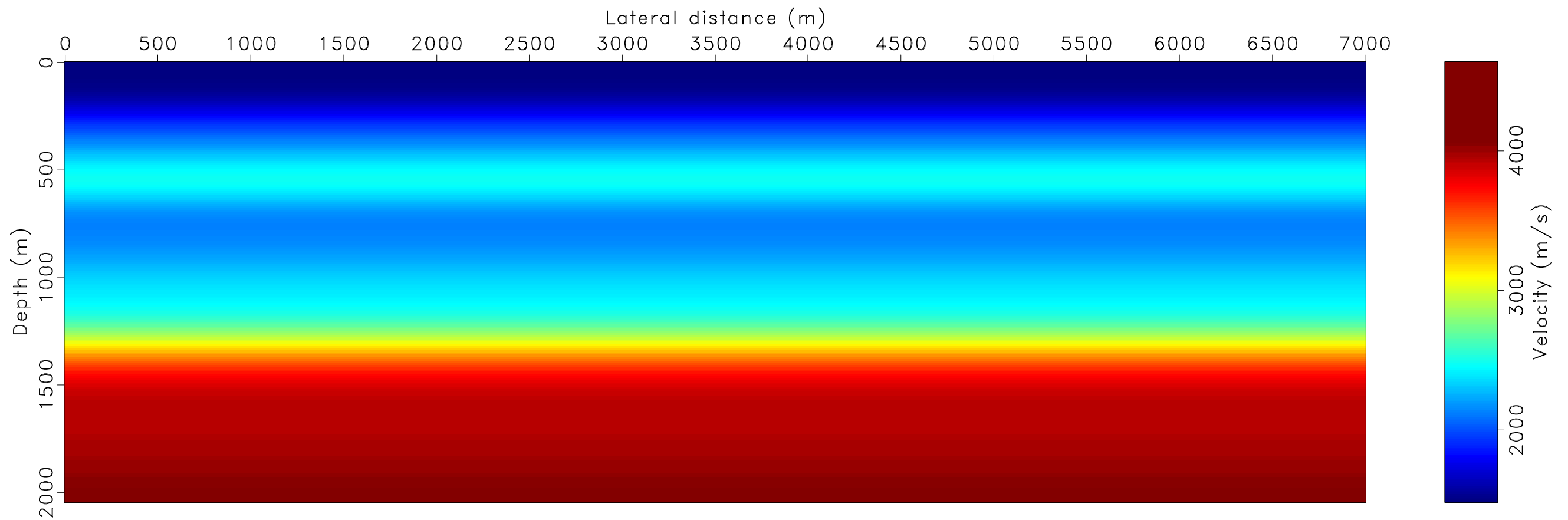
True model

BG compass



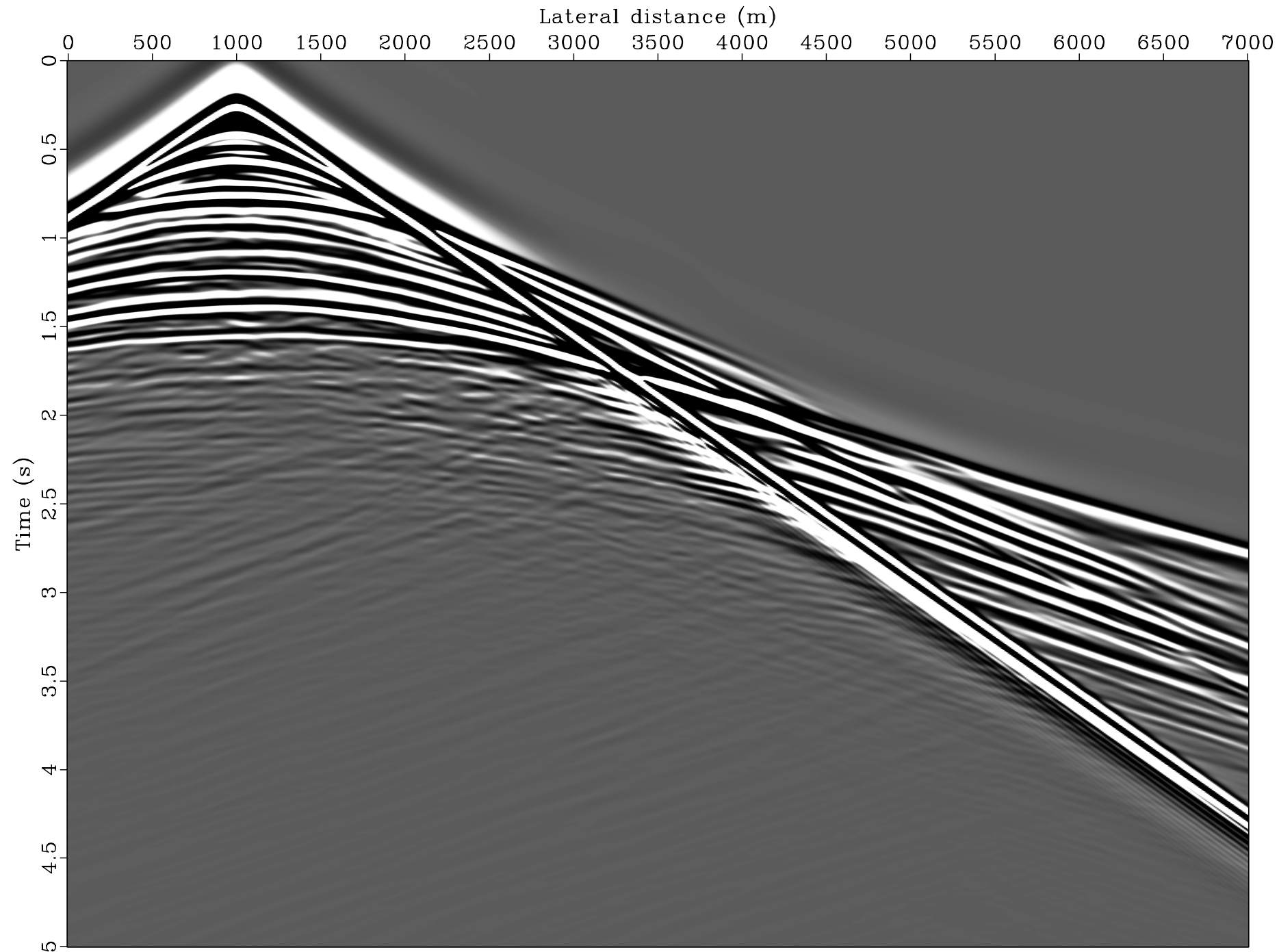
Initial model

Initial model



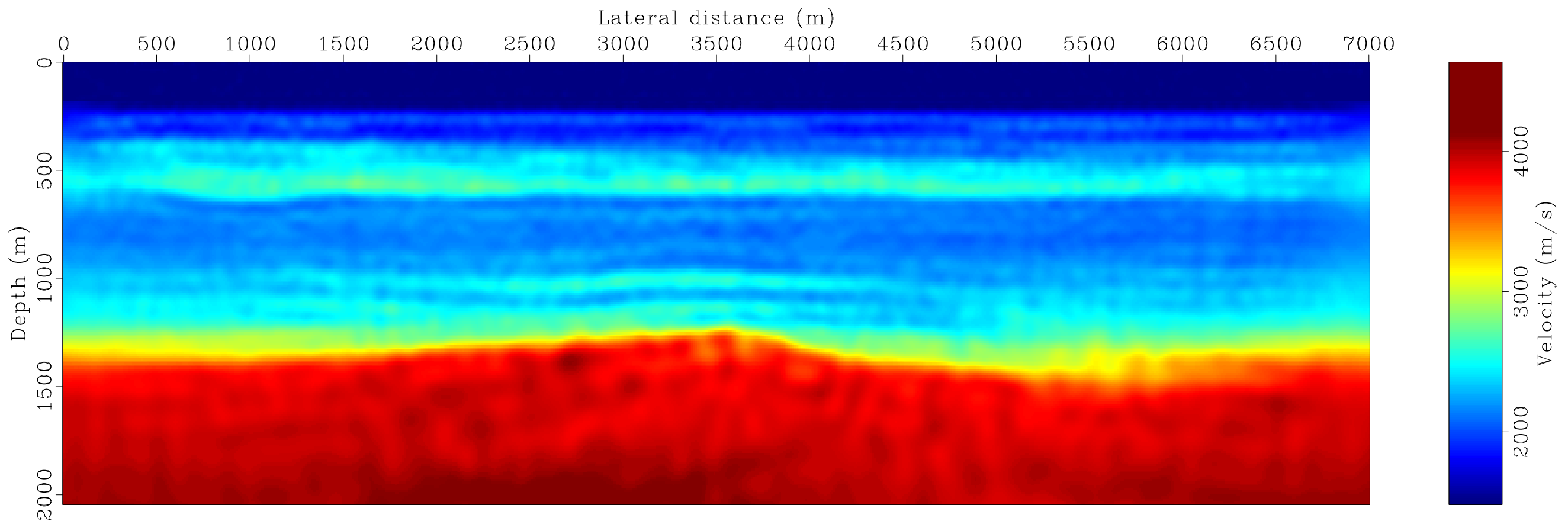
One shot record

Time-domain finite-differences (PML boundary)



Normal Gauss-Newton

Each GN subproblem uses 20 randomly selected sequential shots

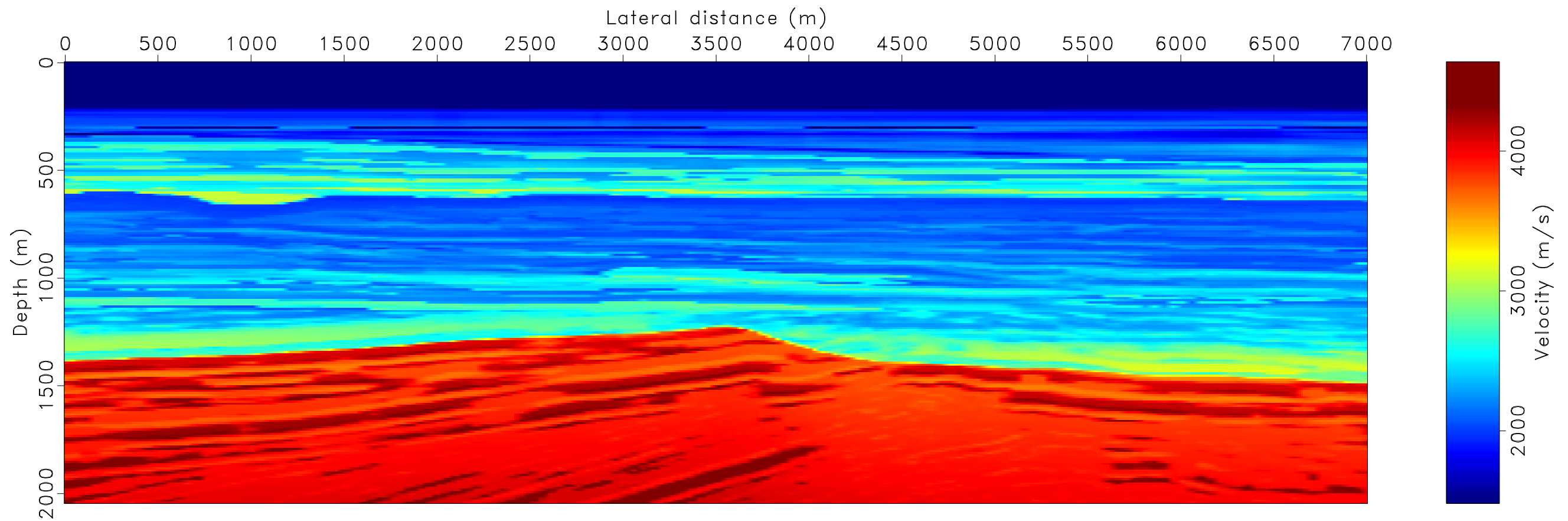


Each GN subproblem using 5 lsqr iterations

1x node, 4 x cpus, an hour

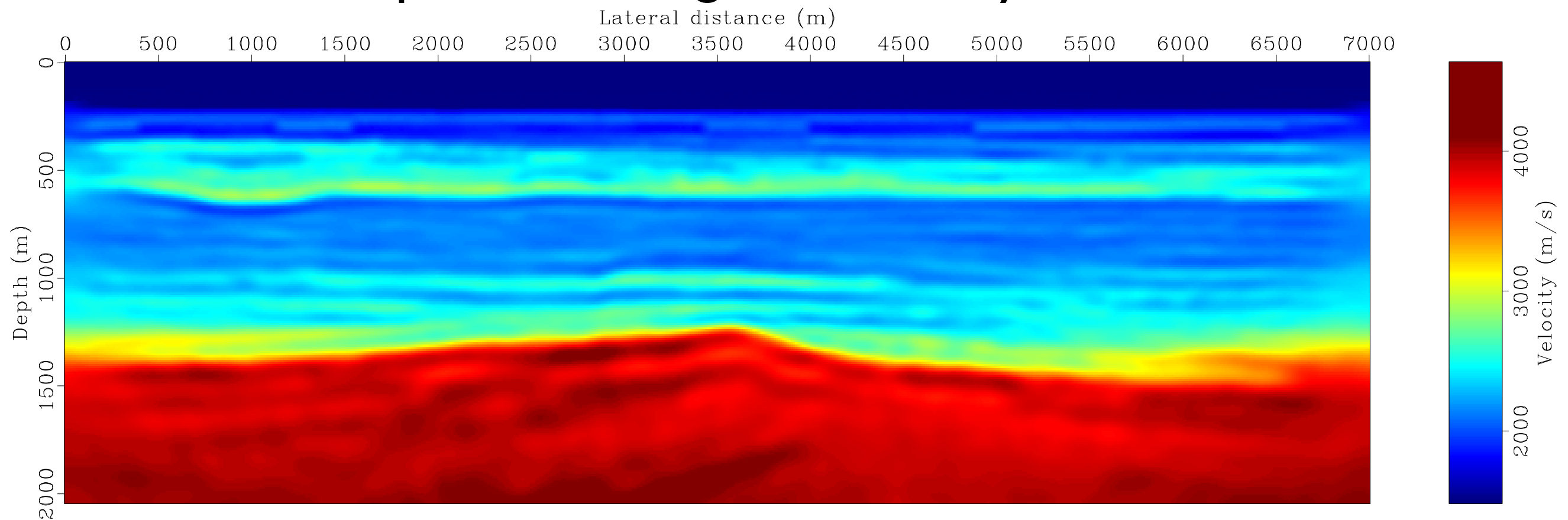
True model

BG compass



Sparsity promoting Gauss-Newton

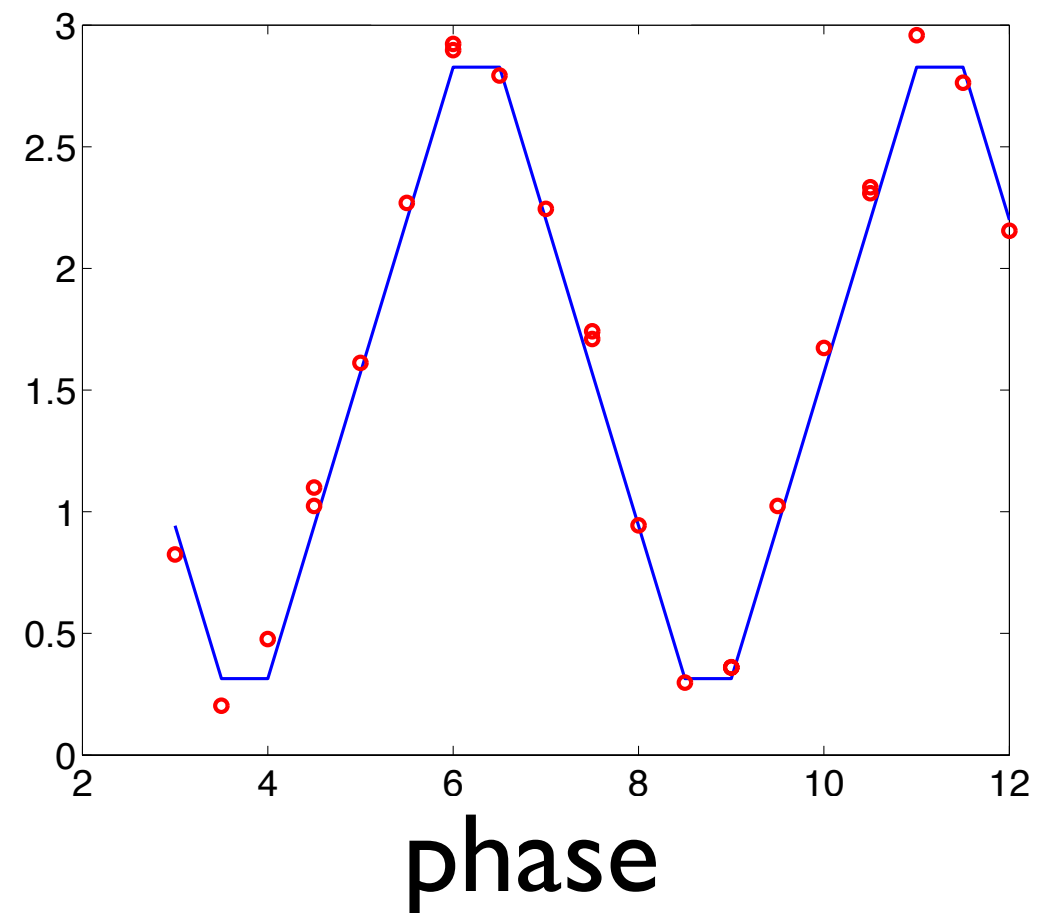
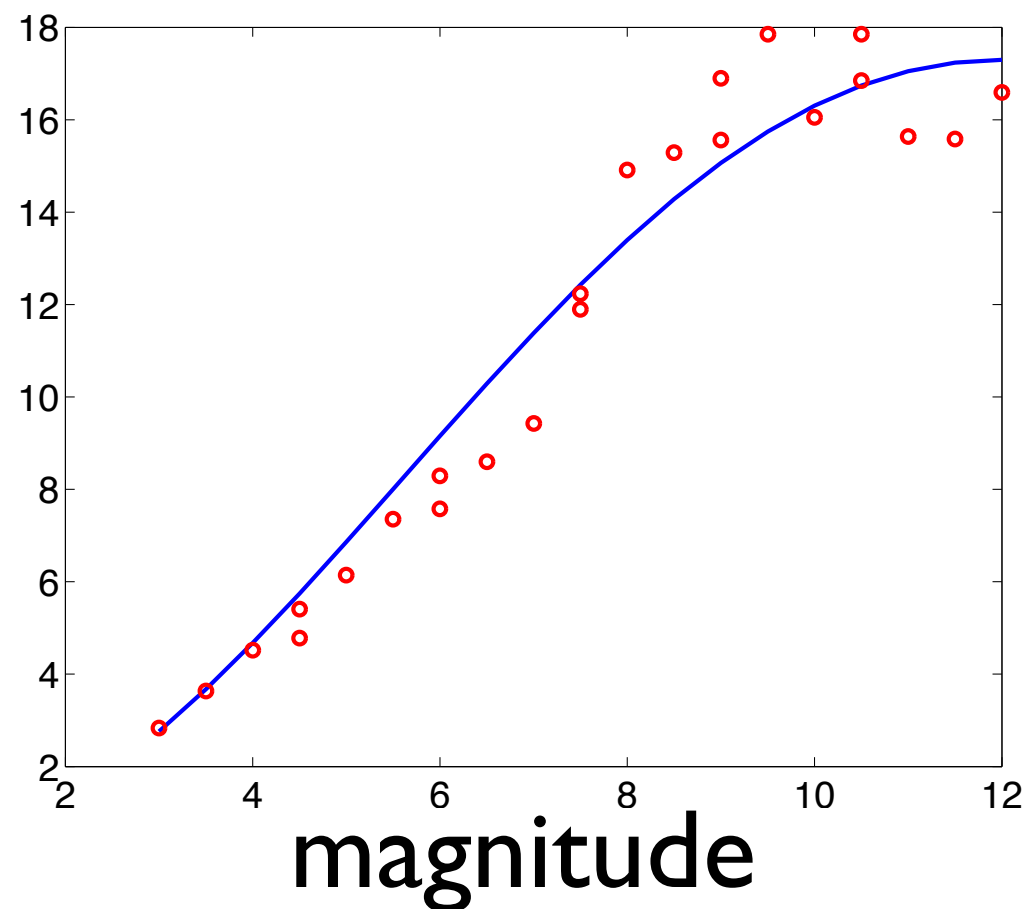
Each GN subproblem using 20 randomly selected shots



Uses <10 spectral-projected gradient iterations

Source wavelet

Estimates source function from 3 to 12 Hz



[Wang & Sacchi, '07]

Seismic imaging

Least-squares migration:

$$\delta\tilde{\mathbf{m}} = \arg \min_{\delta\mathbf{m}} \frac{1}{2} \|\delta\mathbf{d} - \alpha \nabla \mathcal{F}(\mathbf{m}_0) \delta\mathbf{m}\|_2^2$$

$\delta\mathbf{d}$ = Multi-source multi-frequency data residue

$\nabla \mathcal{F}(\mathbf{m}_0)$ = Linearized Born-scattering operator

$\mathbf{m}_0$ = Background velocity model

$\mathbf{Q}$ = Sources

$\delta\tilde{\mathbf{m}}$ = image

[Donoho Chen, '06; Li&Herrmann, '10]

Sparsity-promoting imaging

Basis pursuit denoising problem:

$$\delta \tilde{\mathbf{m}} = \mathbf{C}^T \arg \min_{\delta \mathbf{x}} \|\delta \mathbf{x}\|_{\ell_1} \quad \text{subject to} \quad \|\delta \mathbf{d} - \alpha \nabla \mathcal{F}[\mathbf{m}_0; \mathbf{Q}] \mathbf{C}^T \delta \mathbf{x}\|_2 \leq \sigma$$

$\delta \mathbf{x}$ = Sparse curvelet-coefficient vector

$\mathbf{C}^T$ = Curvelet synthesis

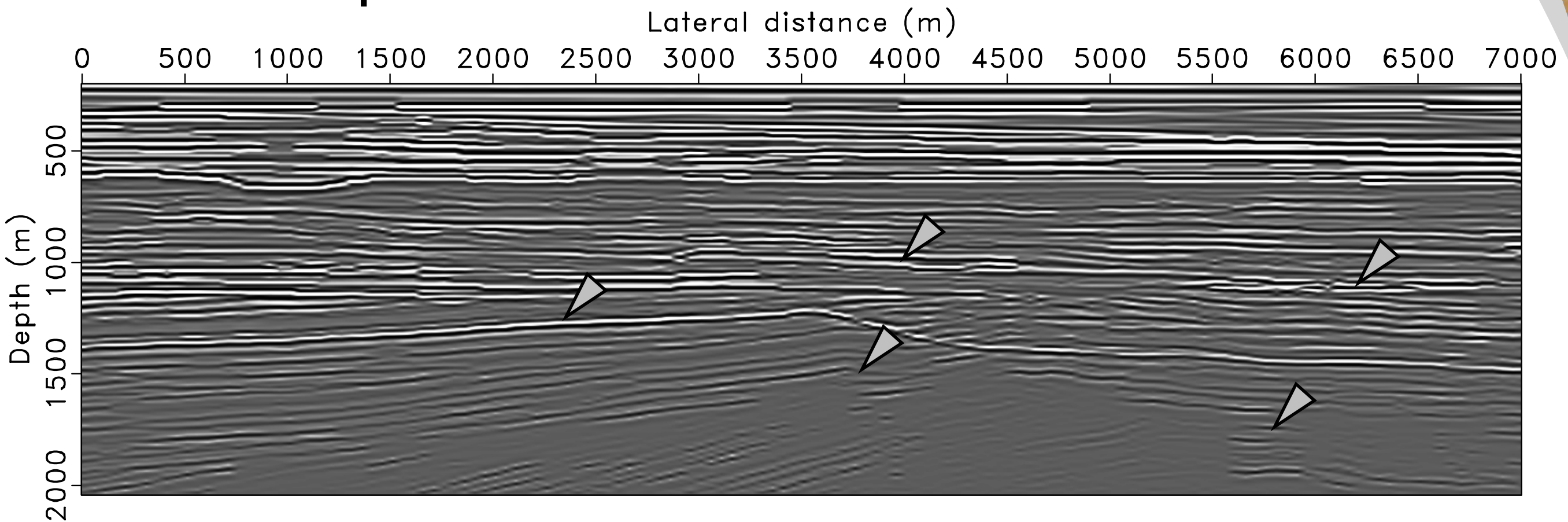
Remarkable speedup of convergence can be obtained by
Message passing

Examples

- 409x1401 with mesh size of 5m
- 10 randomly selected frequencies (30-50Hz)
- 3 randomly combined simultaneous shots / 17 randomly selected sequential shots
- 60 iterations with 10 redraws

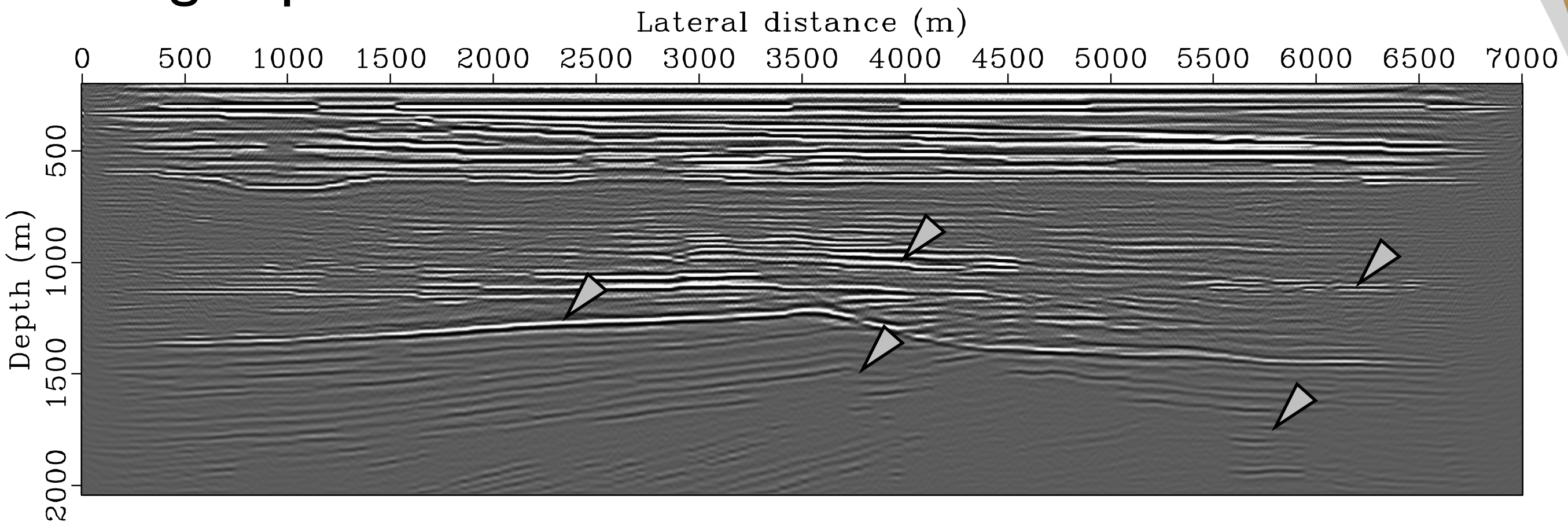
Migration results

True perturbation



Migration results *underdetermined*

imaged perturbation with LI with AMP

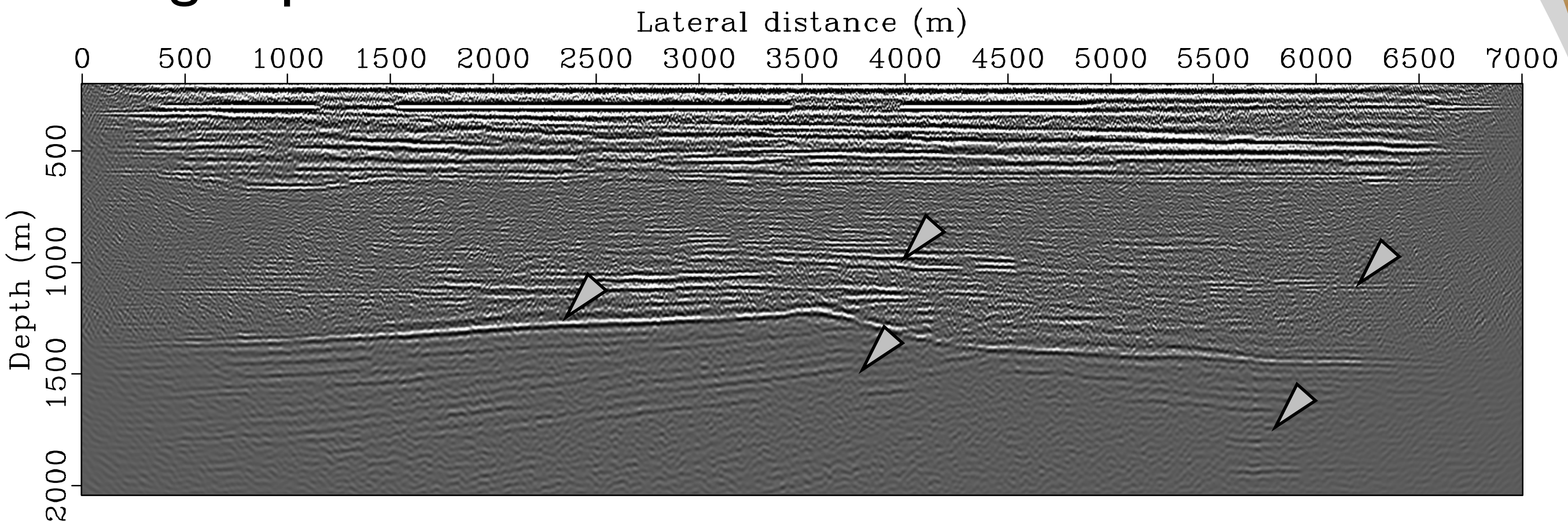


3 simultaneous shots

time: $\sim$ 24 hours

Migration results *underdetermined*

imaged perturbation with L2 with AMP

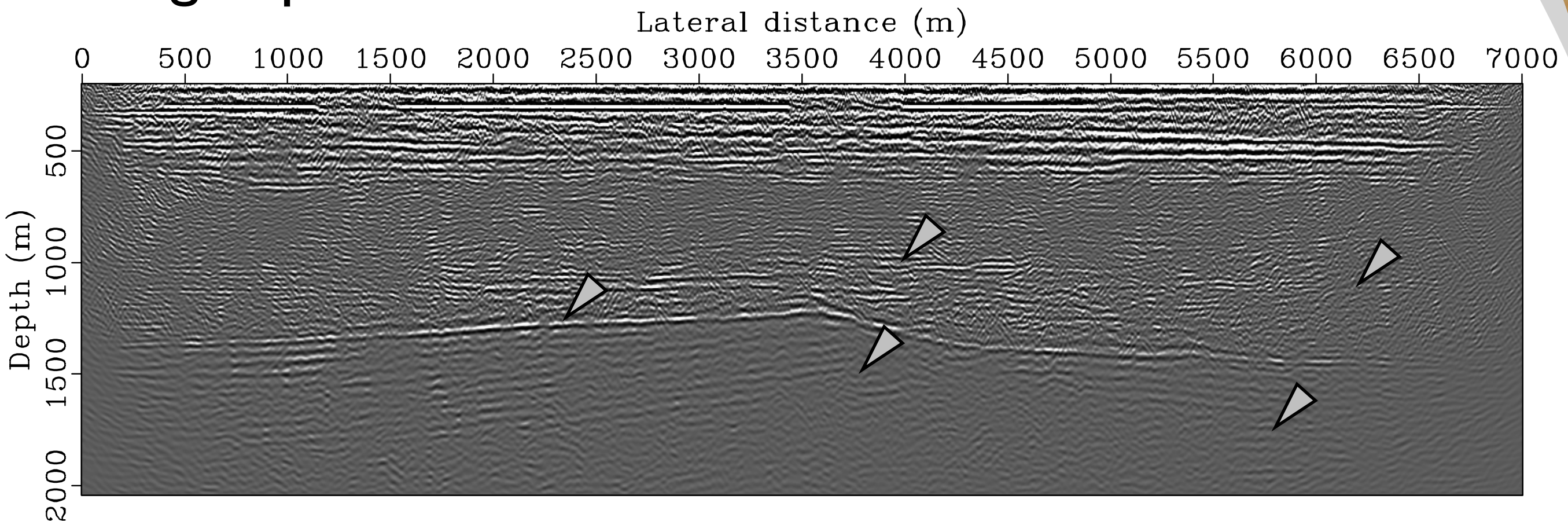


3 simultaneous shots

time: $\sim$ 24 hours

Migration results *underdetermined*

imaged perturbation with LI without AMP

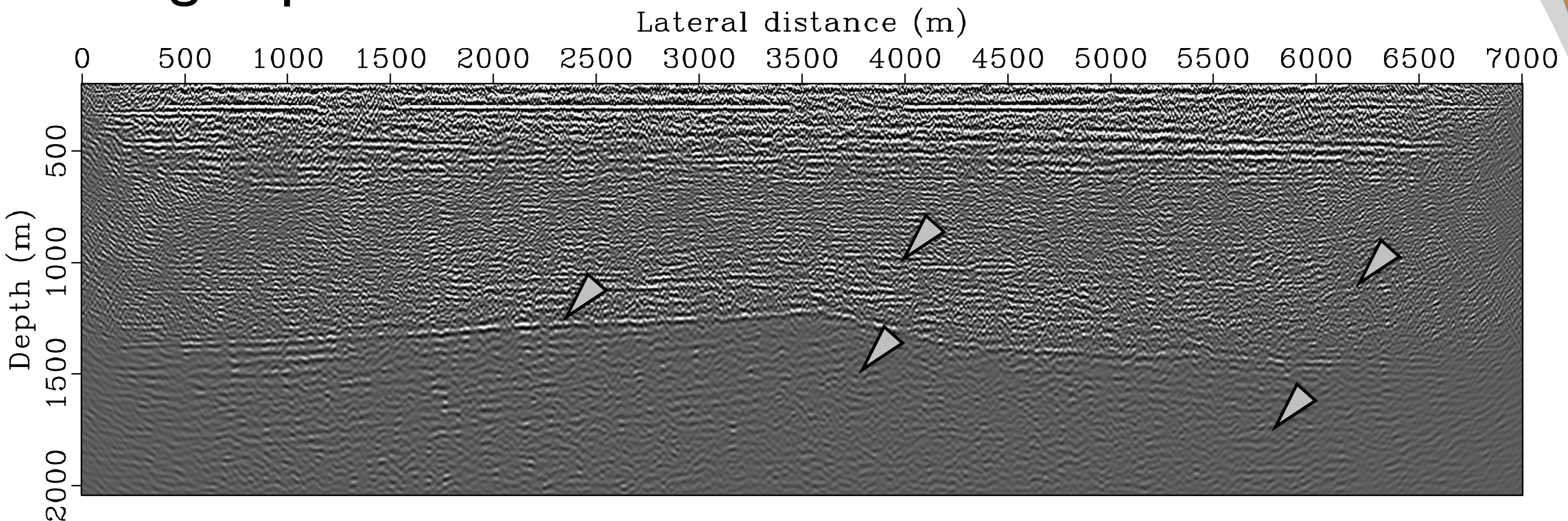


3 simultaneous shots

time: $\sim$ 24 hours

Migration results *underdetermined*

imaged perturbation with L2 without AMP

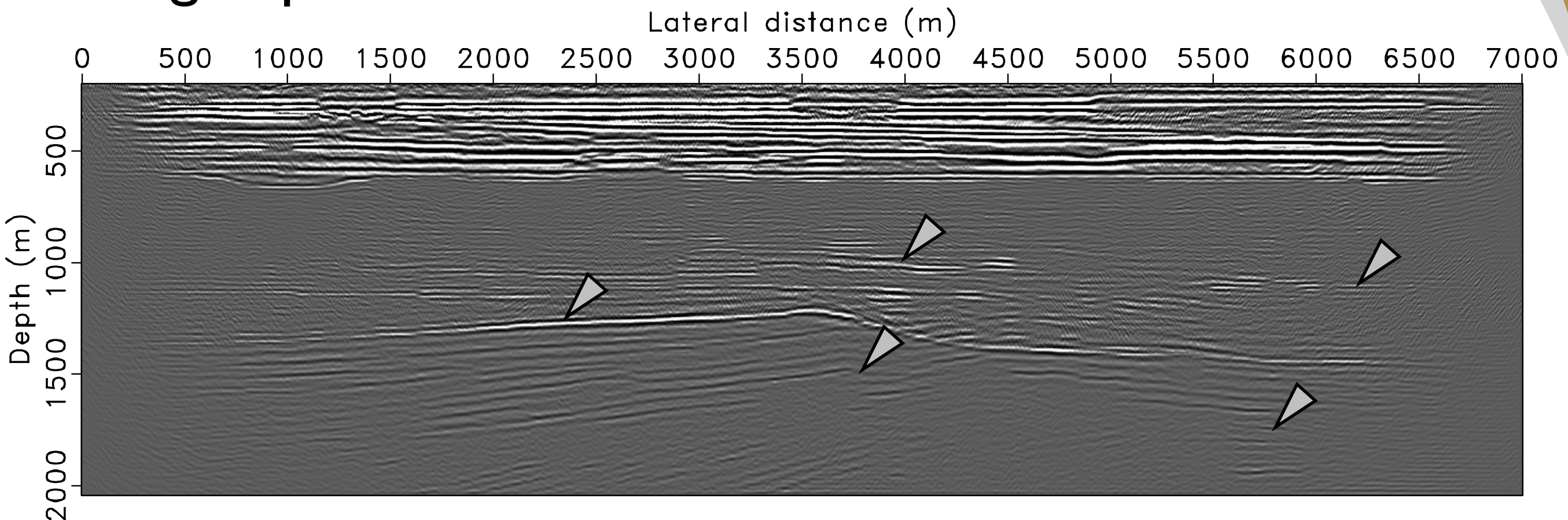


3 simultaneous shots

time: $\sim$ 24 hours

Migration results *underdetermined*

imaged perturbation with LI with AMP

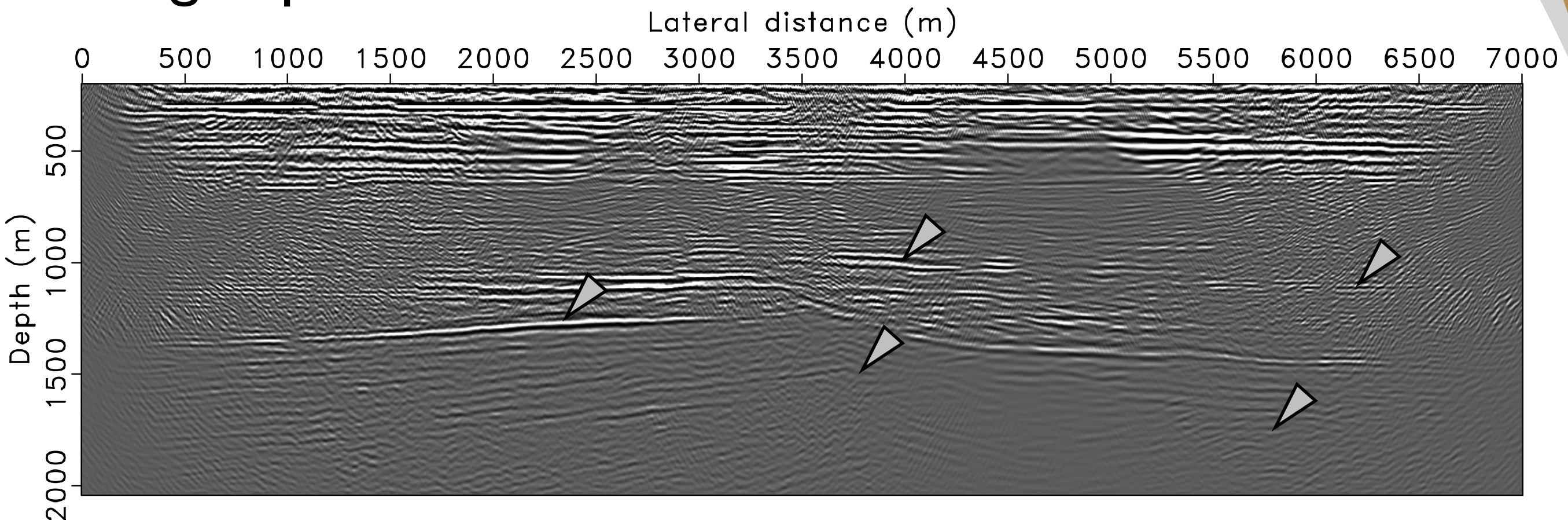


17 sequential shots with
marine acquisition

time: $\sim$ 40 hours

Migration results *underdetermined*

imaged perturbation with LI without AMP



17 sequential shots with
marine acquisition

time: $\sim$ 40 hours

Conclusion

- *Curvelet Transform* is efficiently in representing geological models
- *Sparsity regularization in Curvelet domain* can significantly suppress the model space artifacts
- High-resolution FWI and Imaging results is attainable through Sparsity promotion
- Ideas from message passing leads to a remarkable speedup of convergence

Acknowledgements

- Authors of CurveLab, SPGLI and Spot
- My colleagues

SINBAD



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Thank you

<https://slimweb.eos.ubc.ca/>

Friday, Ballroom C. Workshop: Gulf of Mexico Imaging
Challenges: What can FWI achieve?