

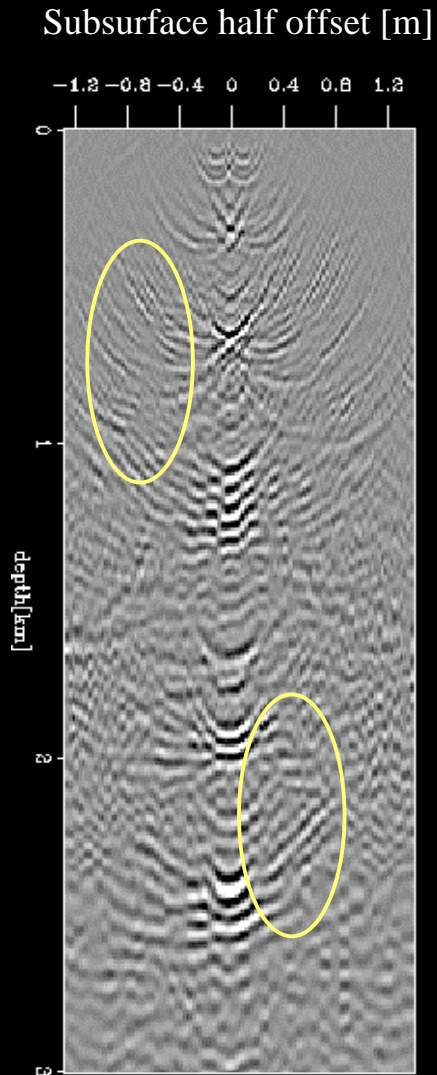
Least-squares migration of incomplete data sets with regularization in the subsurface-offset domain

Yaxun Tang

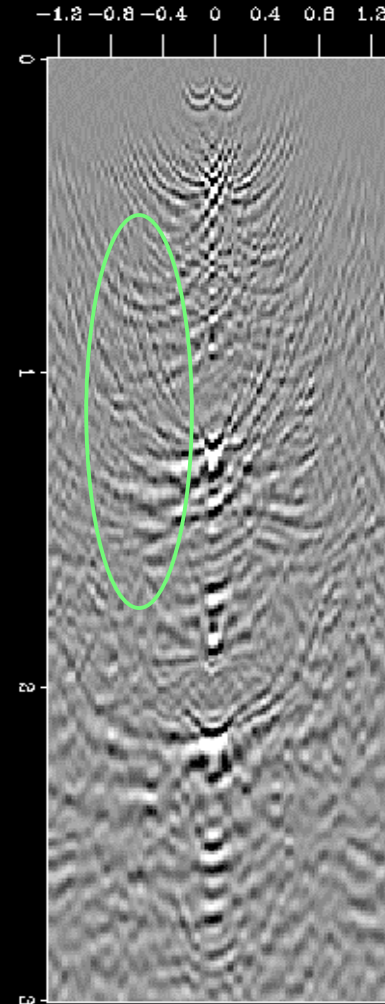
tang@sep.stanford.edu

SEP-125, p159

Comparison of SODCIGs

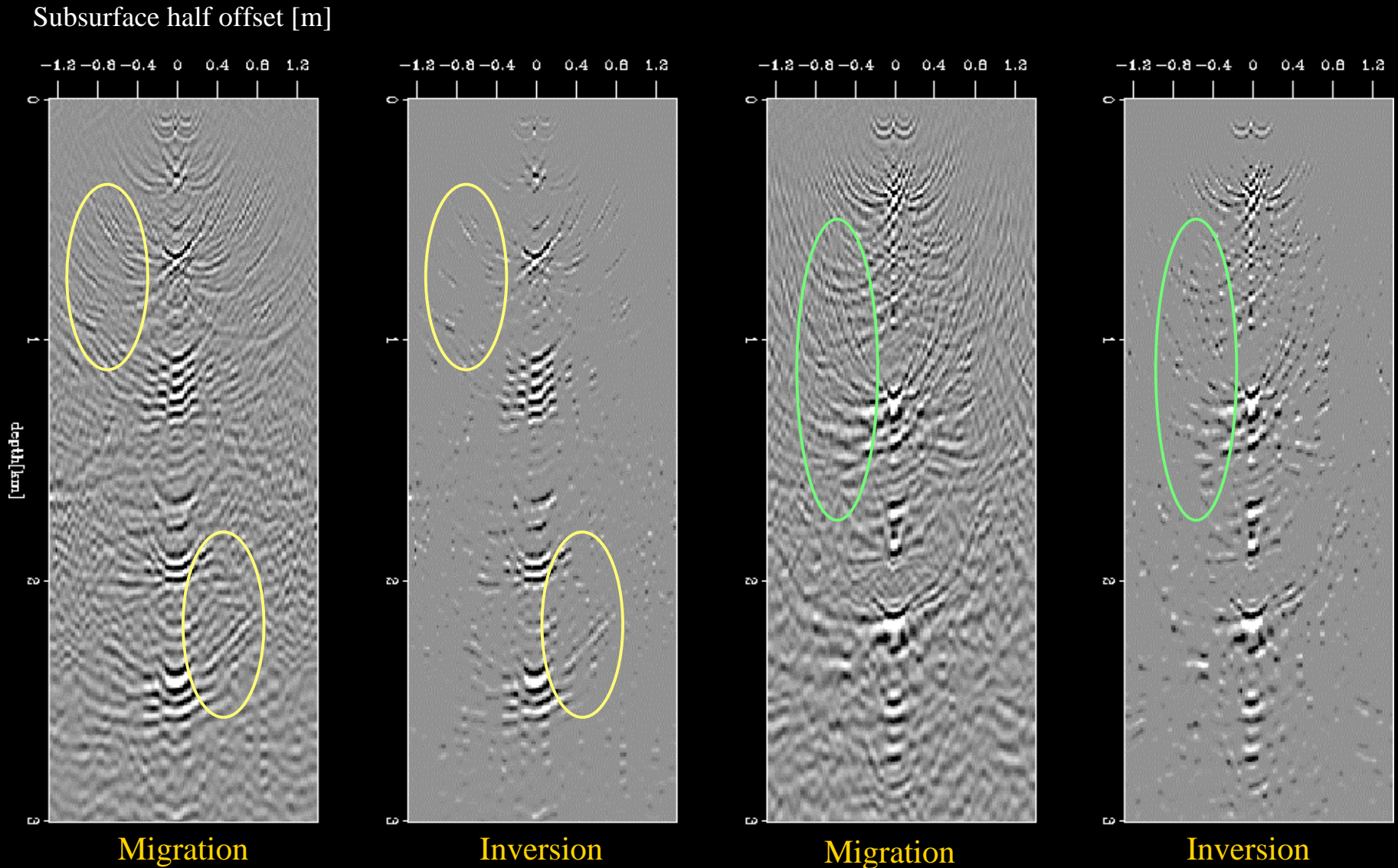


Migration

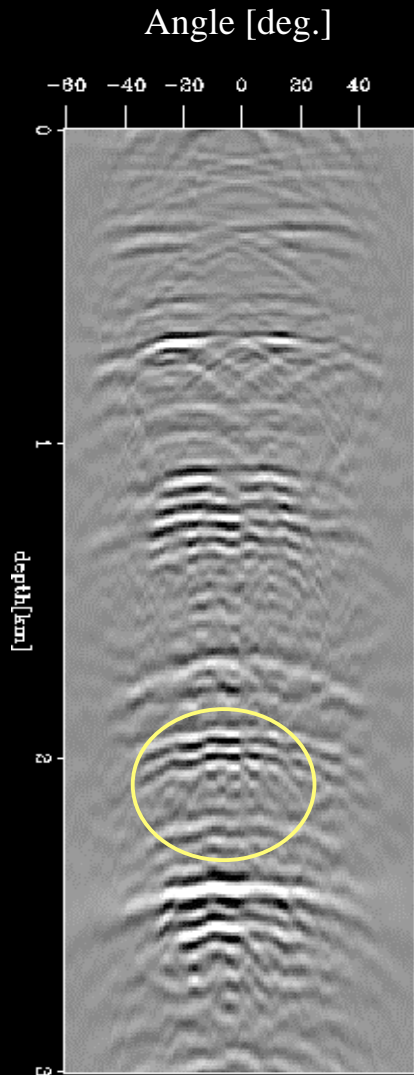


Migration

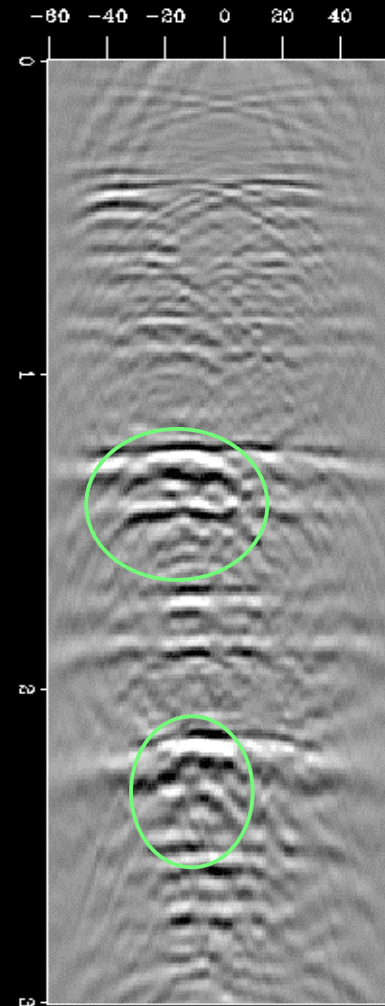
Comparison of SODCIGs



Comparison of ADCIGs

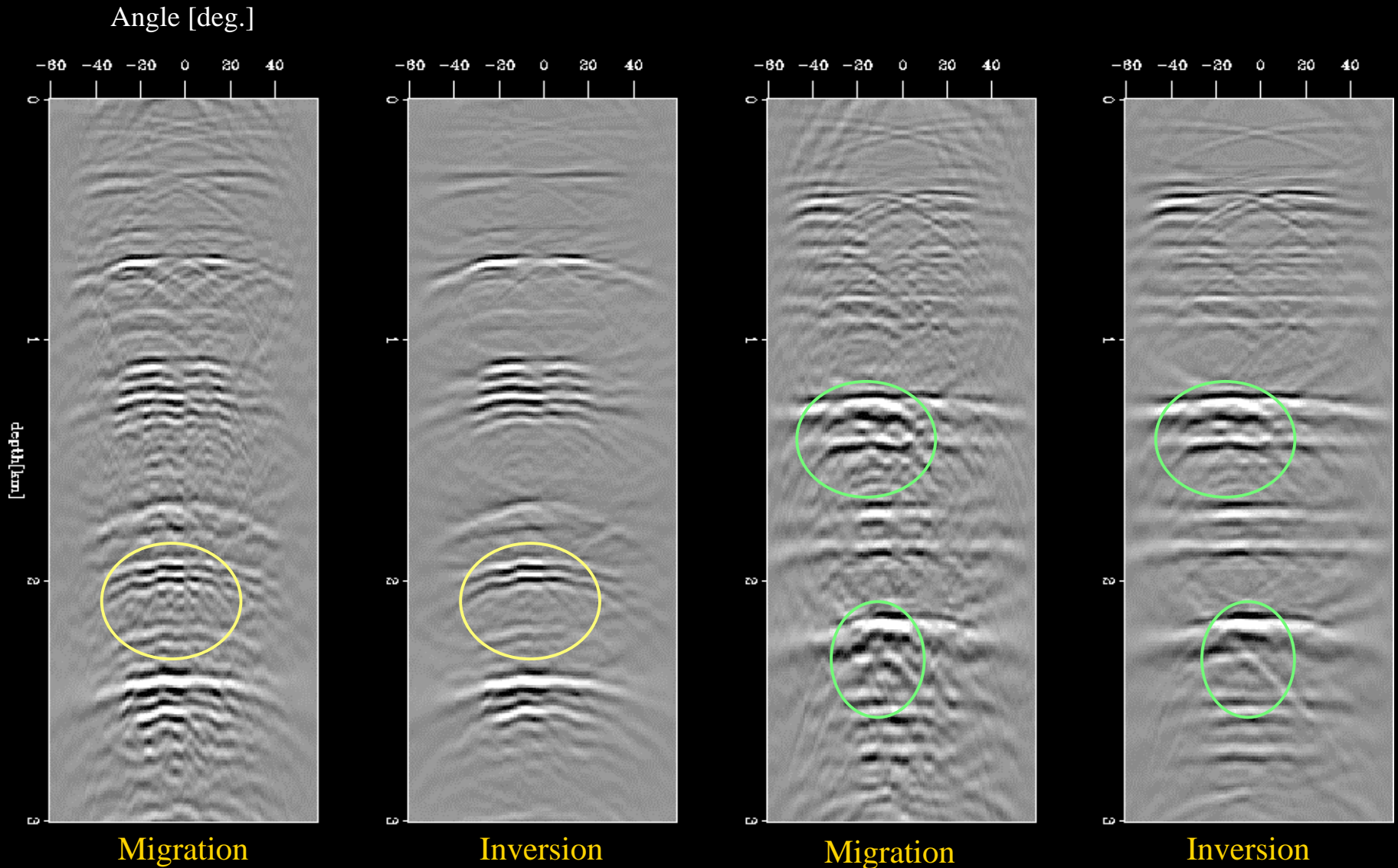


Migration



Migration

Comparison of ADCIGs



Outline

- Regularized inversion theory
- Approximate inversion
- Two-layer synthetic example
- Marmousi example
- Conclusions

Objective functions

Linear operator: $\mathbf{d} = \mathbf{Lm}$

Least-squares
objective function: $J(\mathbf{m}) = \|\mathbf{W}_d(\mathbf{Lm} - \mathbf{d})\|_2$

Regularization: $J(\mathbf{m}) = \|\mathbf{W}_d(\mathbf{Lm} - \mathbf{d})\|_2 + R(\mathbf{m})$

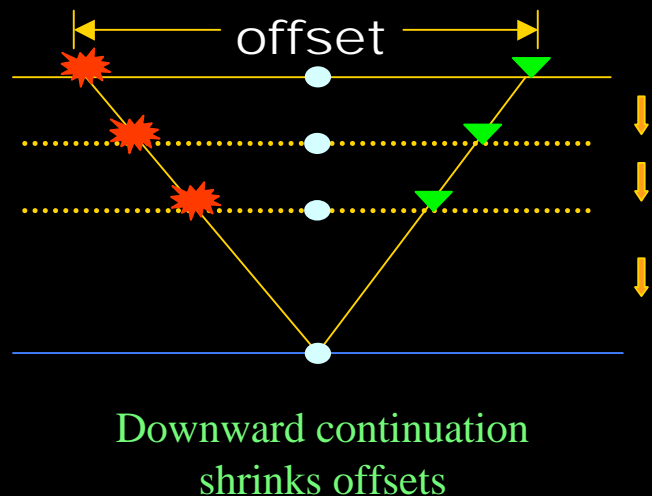
Objective functions

Linear operator: $\mathbf{d} = \mathbf{Lm}$

Least-squares objective function: $J(\mathbf{m}) = \|\mathbf{W}_d(\mathbf{Lm} - \mathbf{d})\|_2$

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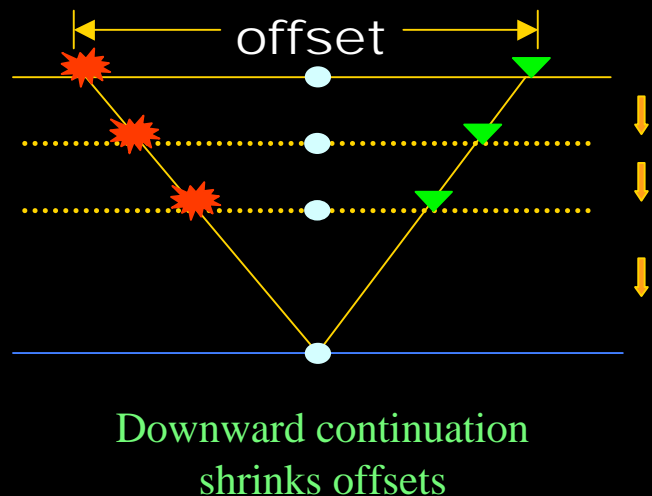
How to choose regularization terms?



Correct velocity + infinite recording geometry

- Energy in the SODCIGs will be focused at zero-offset
- The model space (SODCIGs) should be sparse

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Correct velocity + infinite recording geometry

- Energy in the SODCIGs will be focused at zero-offset
- The model space (SODCIGs) should be sparse

Require regularization terms to:

- Penalize energy at far offset
- Enforce sparseness

in SODCIGs

Penalizing energy at far offsets

- Differential semblance operator, DSO (Shen,2003;Valenciano,2006)
- Multiply h in the subsurface offset domain

$$D(\mathbf{m}) = \text{diag}(|\mathbf{h}|)\mathbf{m}$$

$$\text{diag}(|\mathbf{h}|) = \text{diag}(|h_1|, |h_2|, \dots, |h_m|)$$

- DSO in SODCIGs has the same effect as smoothing along ray-parameter in ADCIGs

Forcing SODCIGs to be sparse

- Sparseness constraint (Cauchy norm or L1 norm)
- Sparseness in stacked offset-ray-parameter domain (Wang and Sacchi, 2007)
- Instead, I propose to add sparseness weights in SODCIGs directly

$$W_{si} = \frac{1}{\sqrt{1 + (D(m_i)/\sigma)^2}}$$

Cauchy norm

Proposed inversion scheme

Fitting goals:

$$\mathbf{0} \approx \mathbf{W}_d (\mathbf{Lm} - \mathbf{d})$$

$$\mathbf{0} \approx \varepsilon \mathbf{W}_s D(\mathbf{m})$$

$$D(\mathbf{m}) = \text{diag}(|\mathbf{h}|)\mathbf{m}$$

$$\text{diag}(|\mathbf{h}|) = \text{diag}(|h_1|, |h_2|, \dots, |h_m|)$$

Differential
semblance
operator (DSO)

$$W_{si} = \frac{1}{\sqrt{1 + (D(m_i)/\sigma)^2}}$$

Sparseness
constraints

Re-formulating the problem

- The cost for one iteration equals to two migrations
- Re-formulate the problem as follows

$$\mathbf{0} \approx \mathbf{W}_d (\mathbf{Lm} - \mathbf{d})$$

$$\mathbf{0} \approx \varepsilon \mathbf{W}_s D(\mathbf{m})$$



$$\mathbf{0} \approx \mathbf{Hm} - \mathbf{m}_{\text{mig}}$$

$$\mathbf{0} \approx \varepsilon \mathbf{W}_s D(\mathbf{m})$$

Approximating the Hessian

- Target-oriented Hessian via computing the Green's functions (Valenciano and Biondi, 2004)
- Approximating Hessian via reference images (Rickett, 2003)

$$\mathbf{H} \approx \mathbf{W}_H = \frac{\text{diag}(\mathbf{L}'\mathbf{W}_d'\mathbf{W}_d\mathbf{L}\mathbf{m}_{\text{ref}})}{\text{diag}(\mathbf{m}_{\text{ref}})}$$

Approximated inversion scheme

$$\mathbf{0} \approx \mathbf{W}_H \mathbf{m} - \mathbf{m}_{\text{mig}}$$

$$\mathbf{0} \approx \varepsilon \mathbf{W}_s D(\mathbf{m})$$

\mathbf{W}_H : approximated Hessian

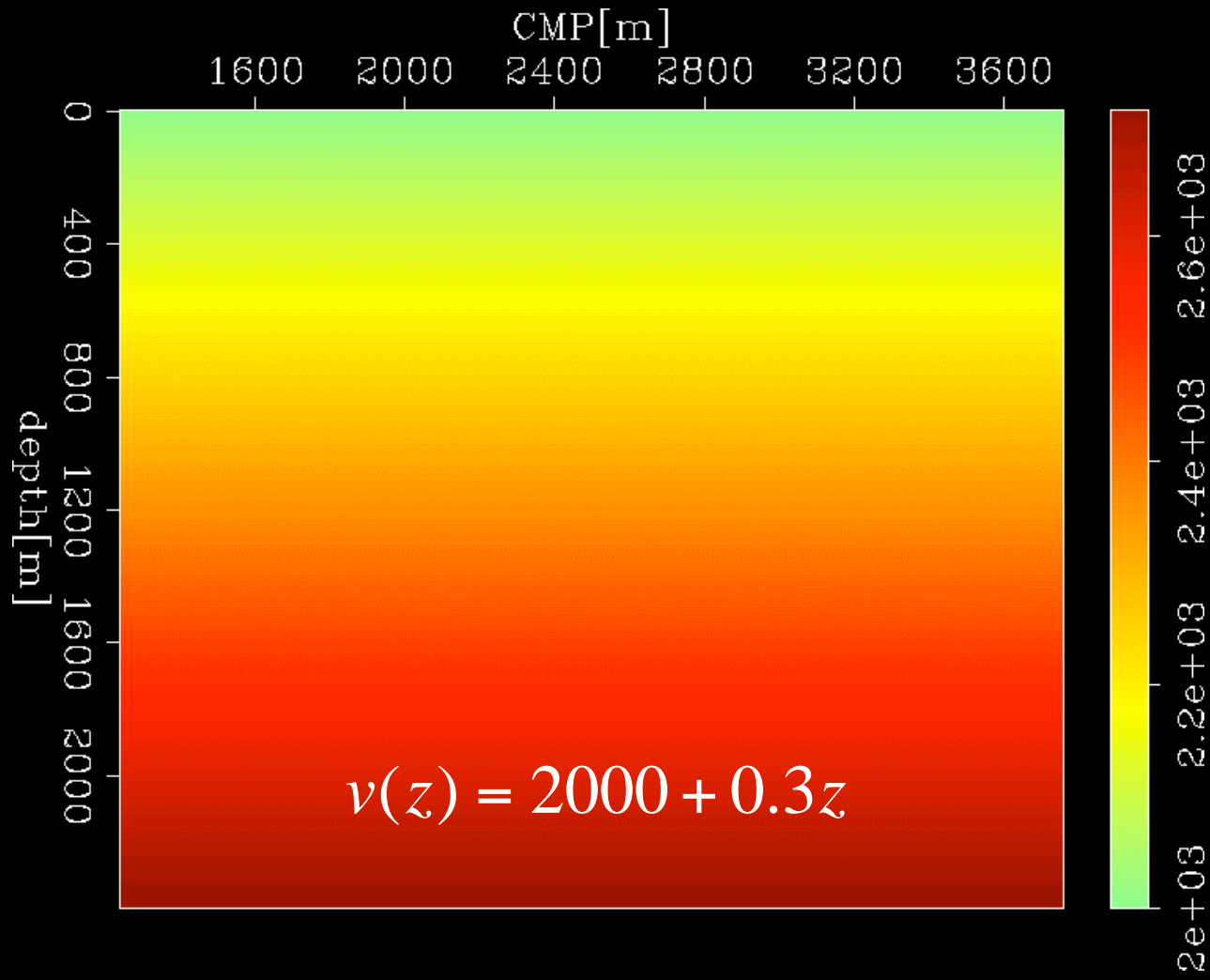
D : differential semblance

\mathbf{W}_s : sparseness weights

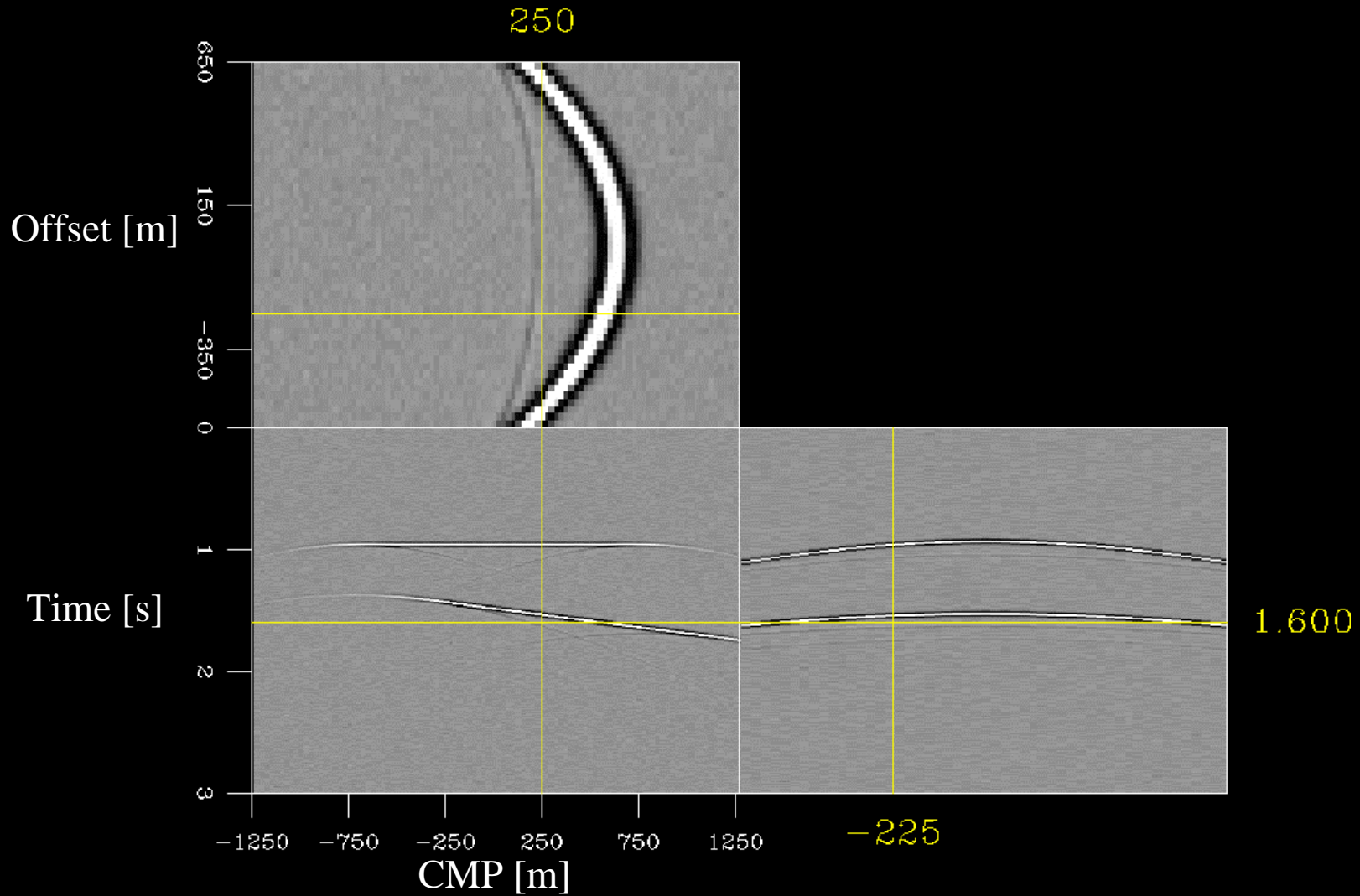
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- **Two-layer synthetic example**
- Marmousi example
- Conclusions

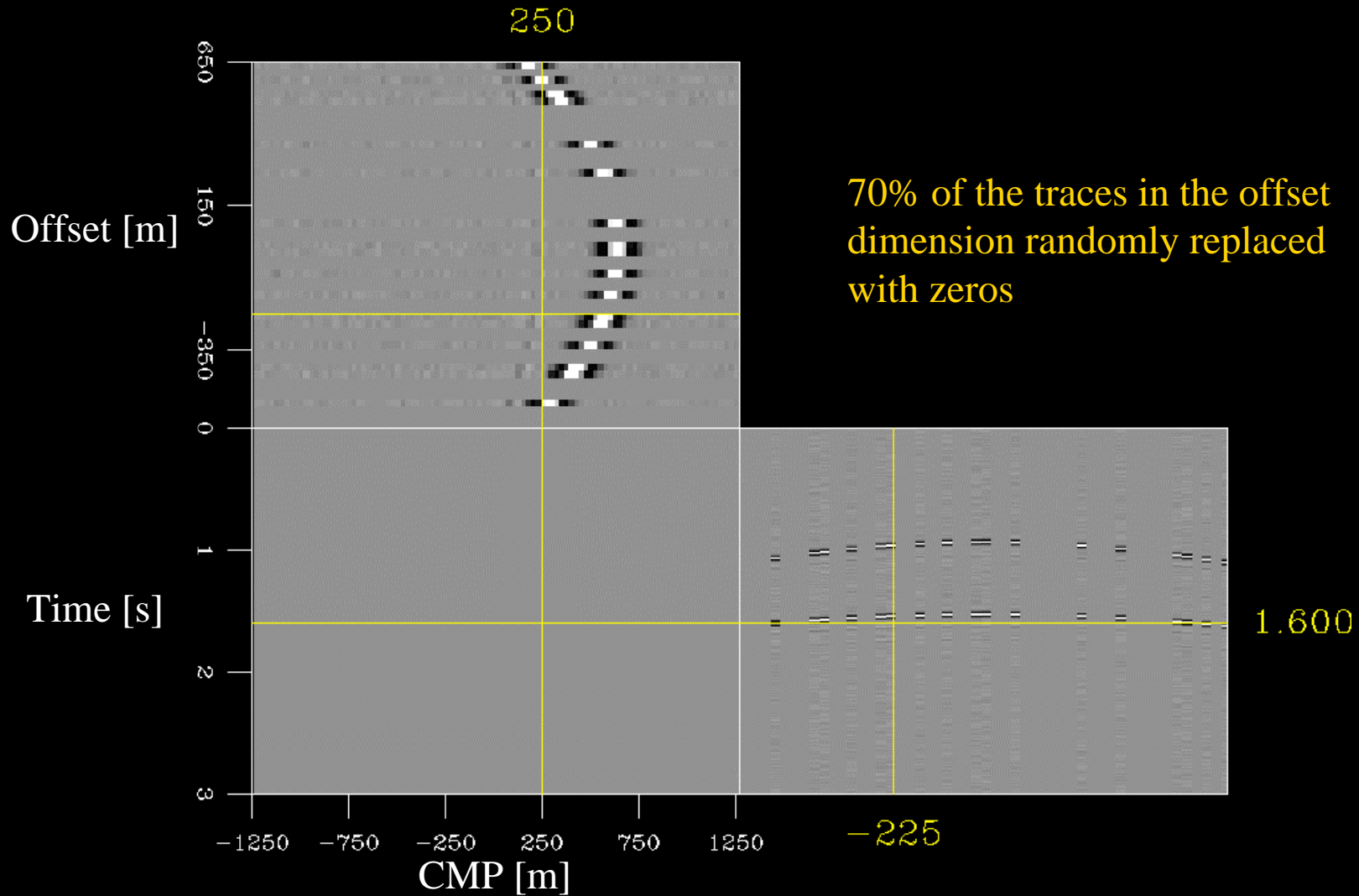
V(z) velocity model



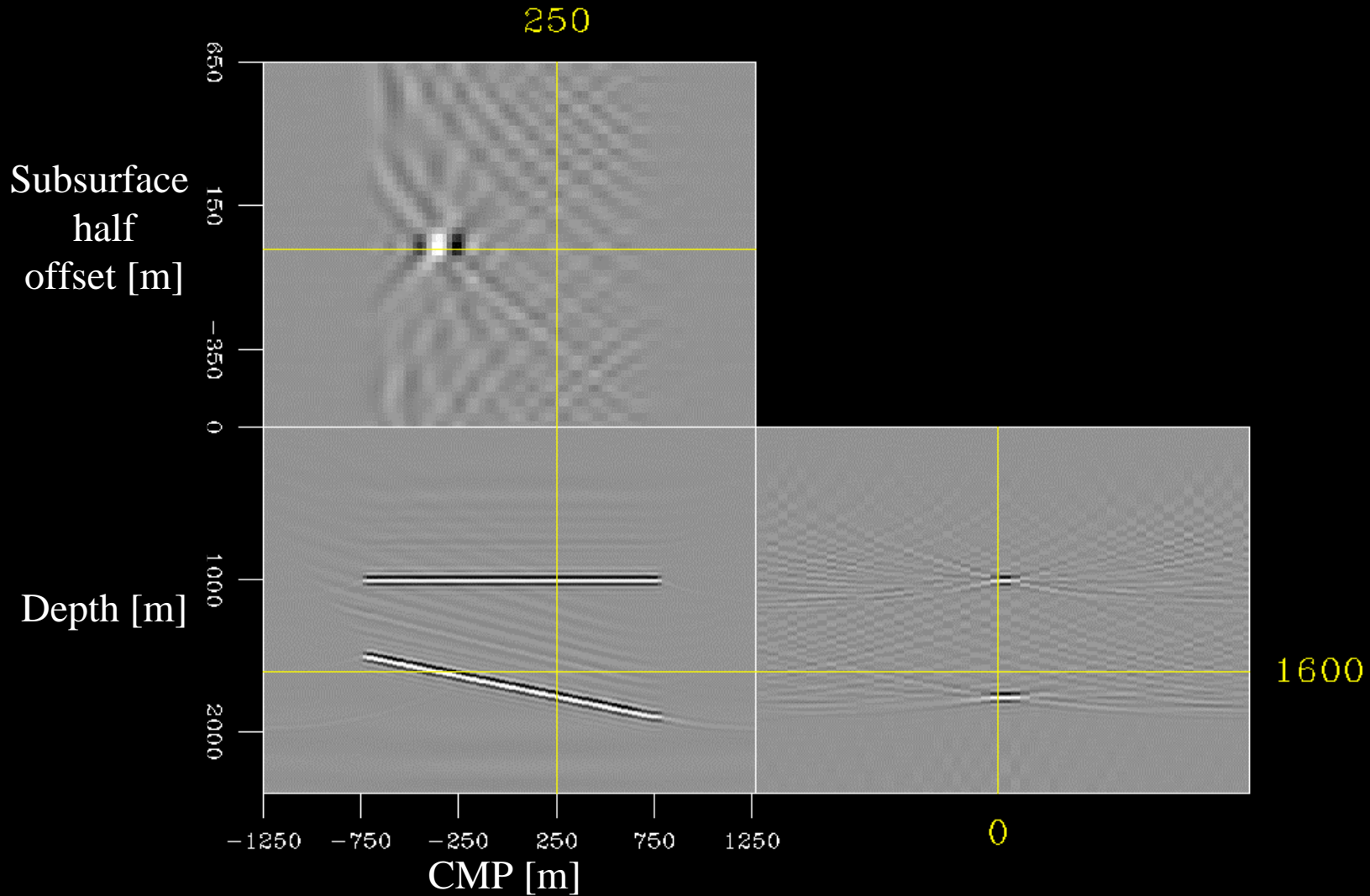
Synthetic data



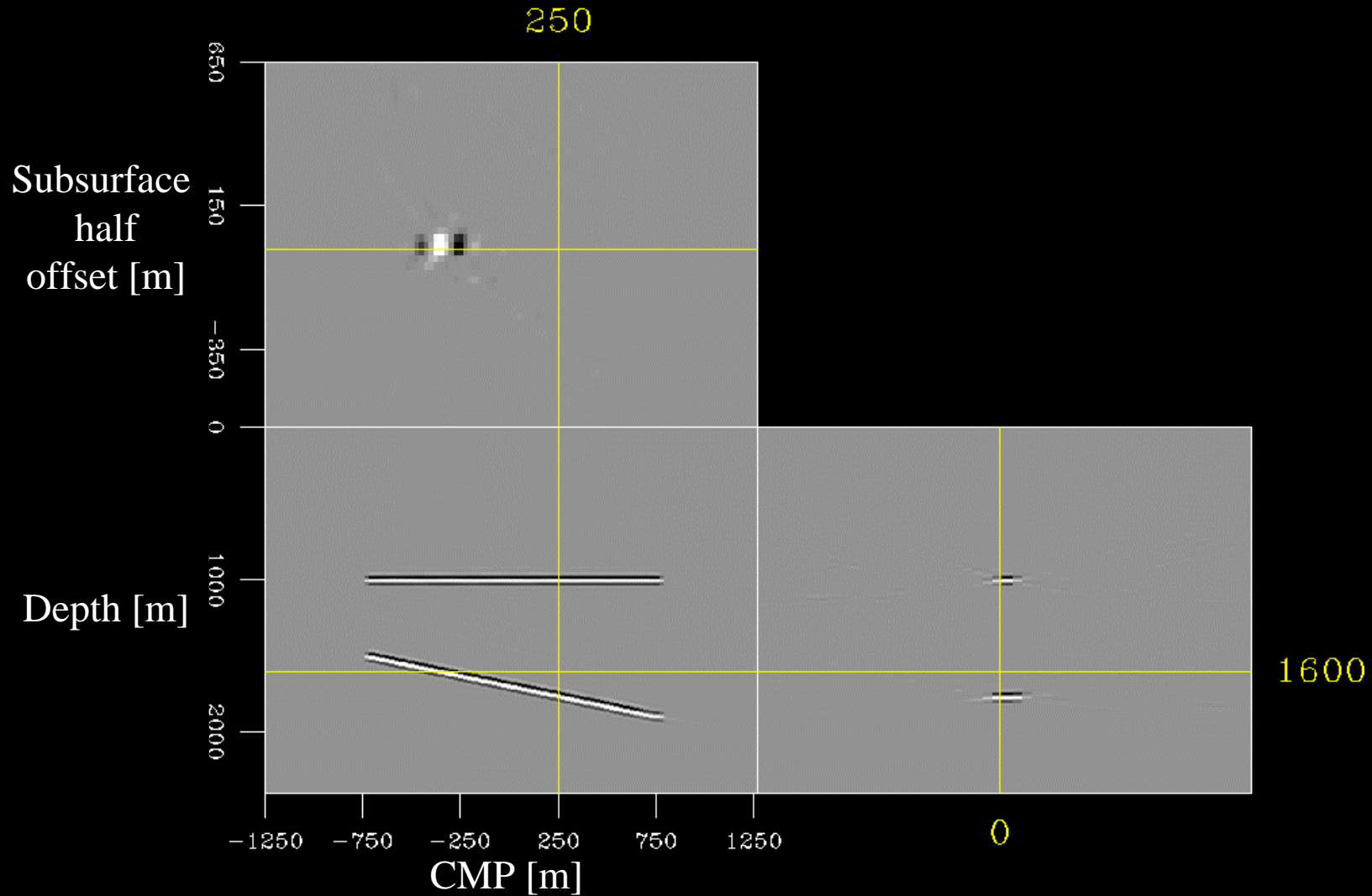
Decimated data



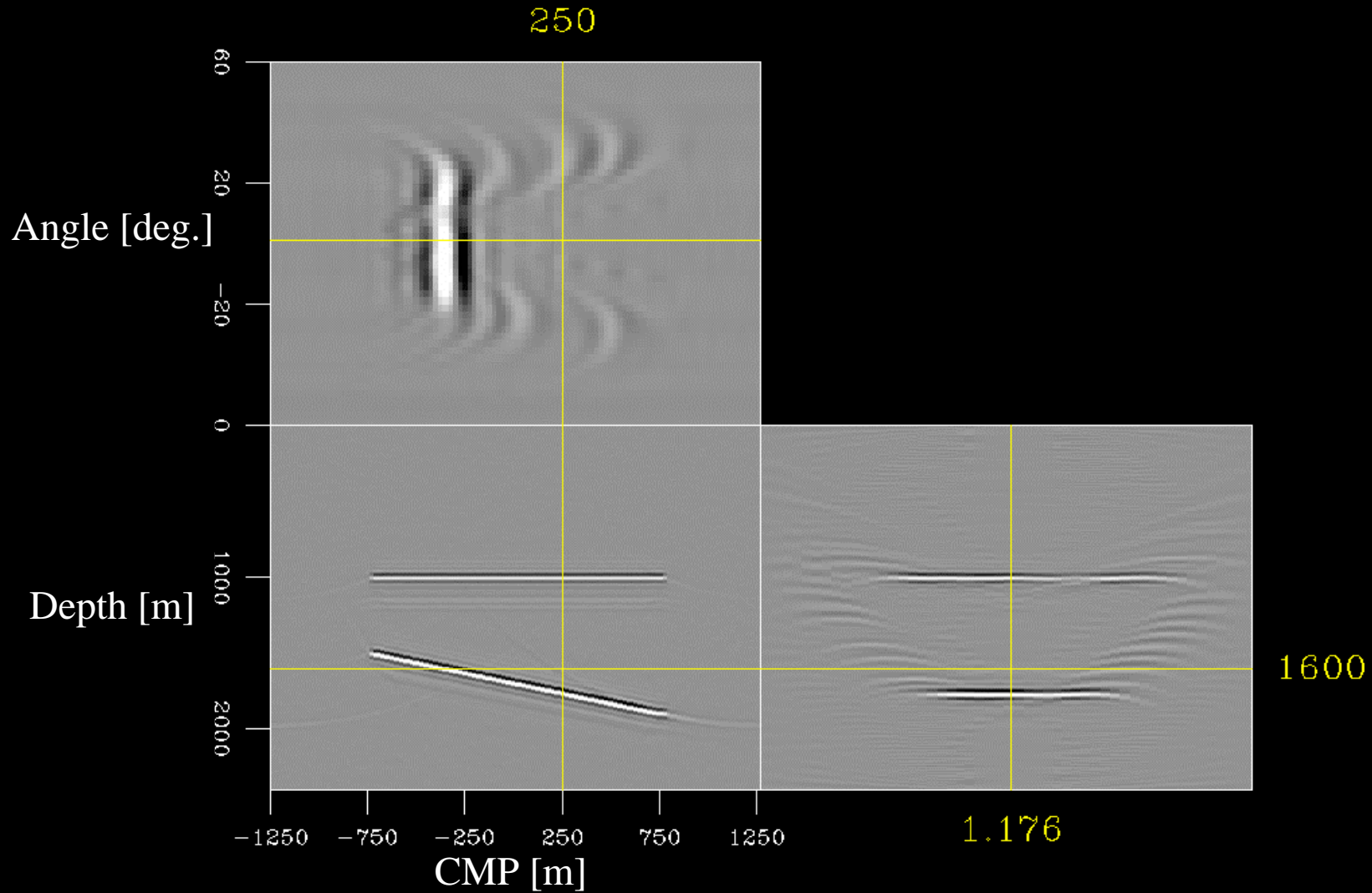
Migrated SODCIGs



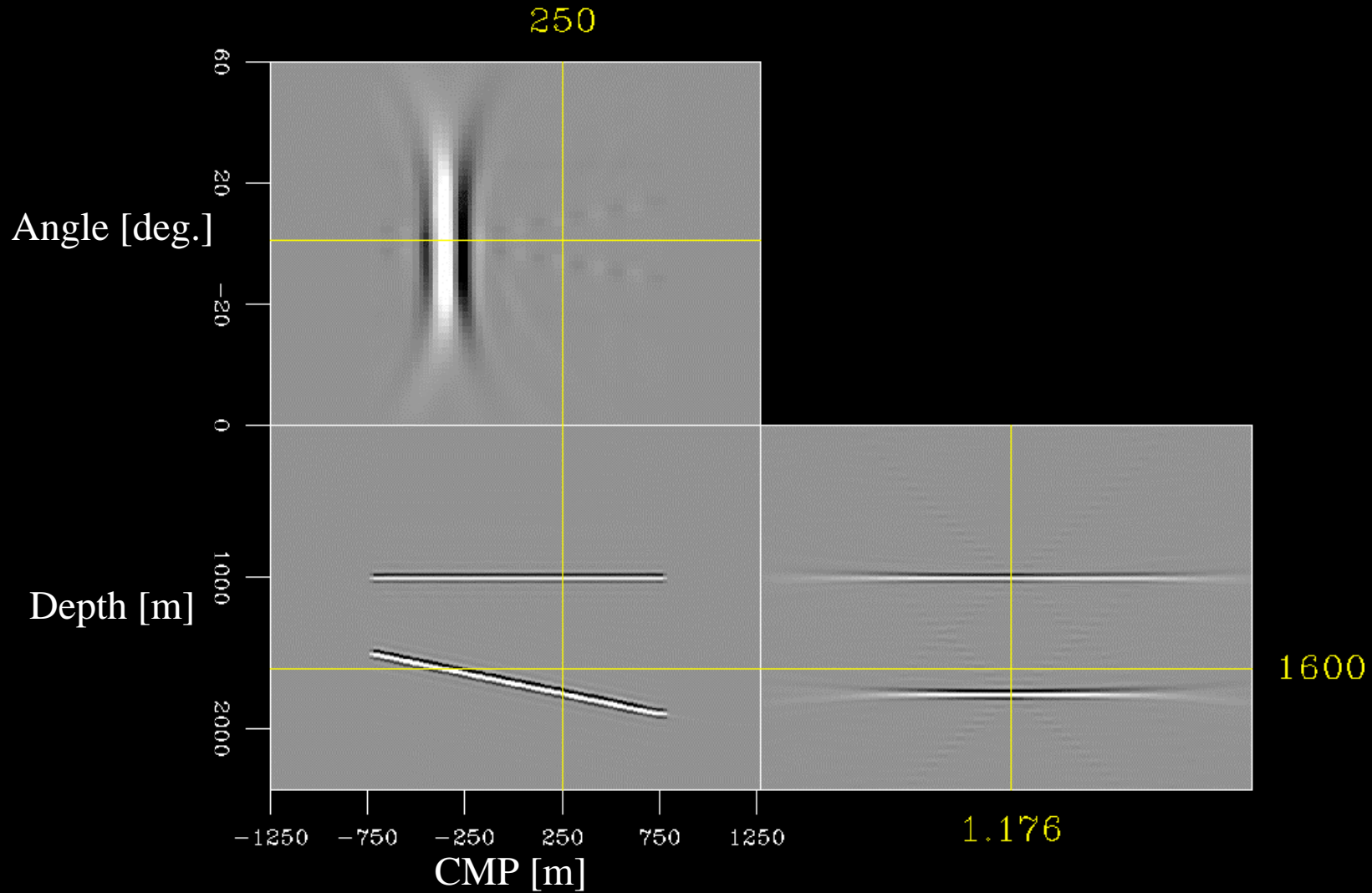
Inverted SODCIGs



Migrated ADCIGs

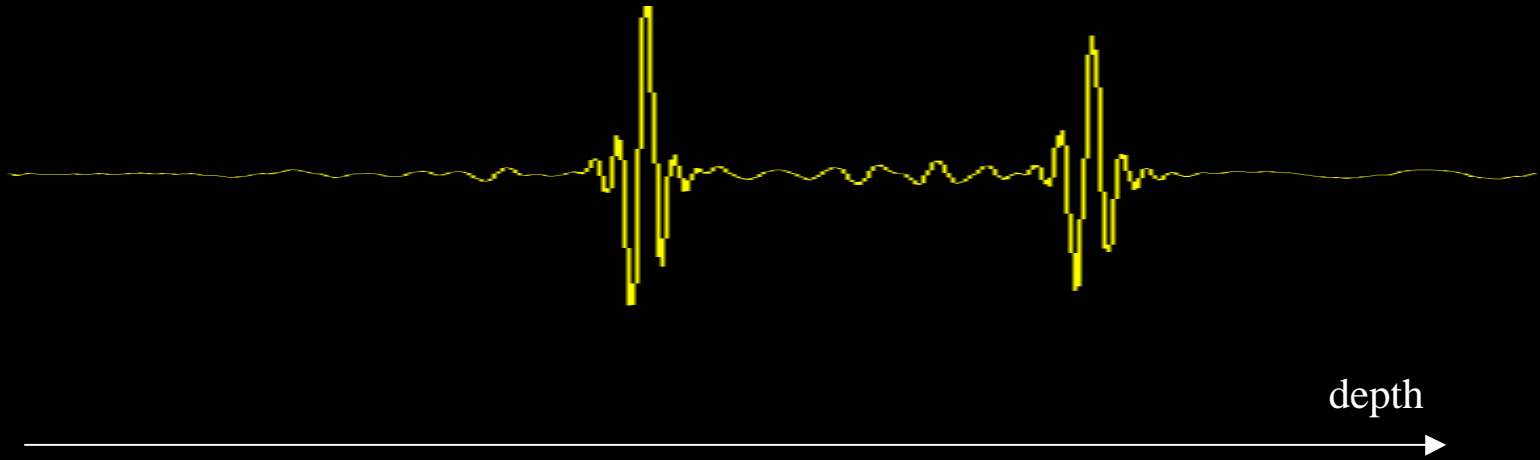


Inverted ADCIGs

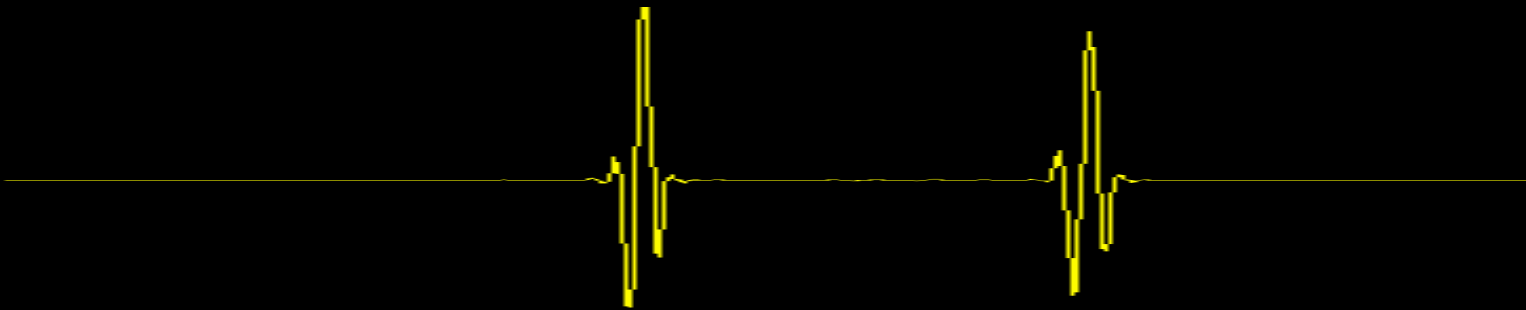


Traces at CMP=0 & offset=0

Migration



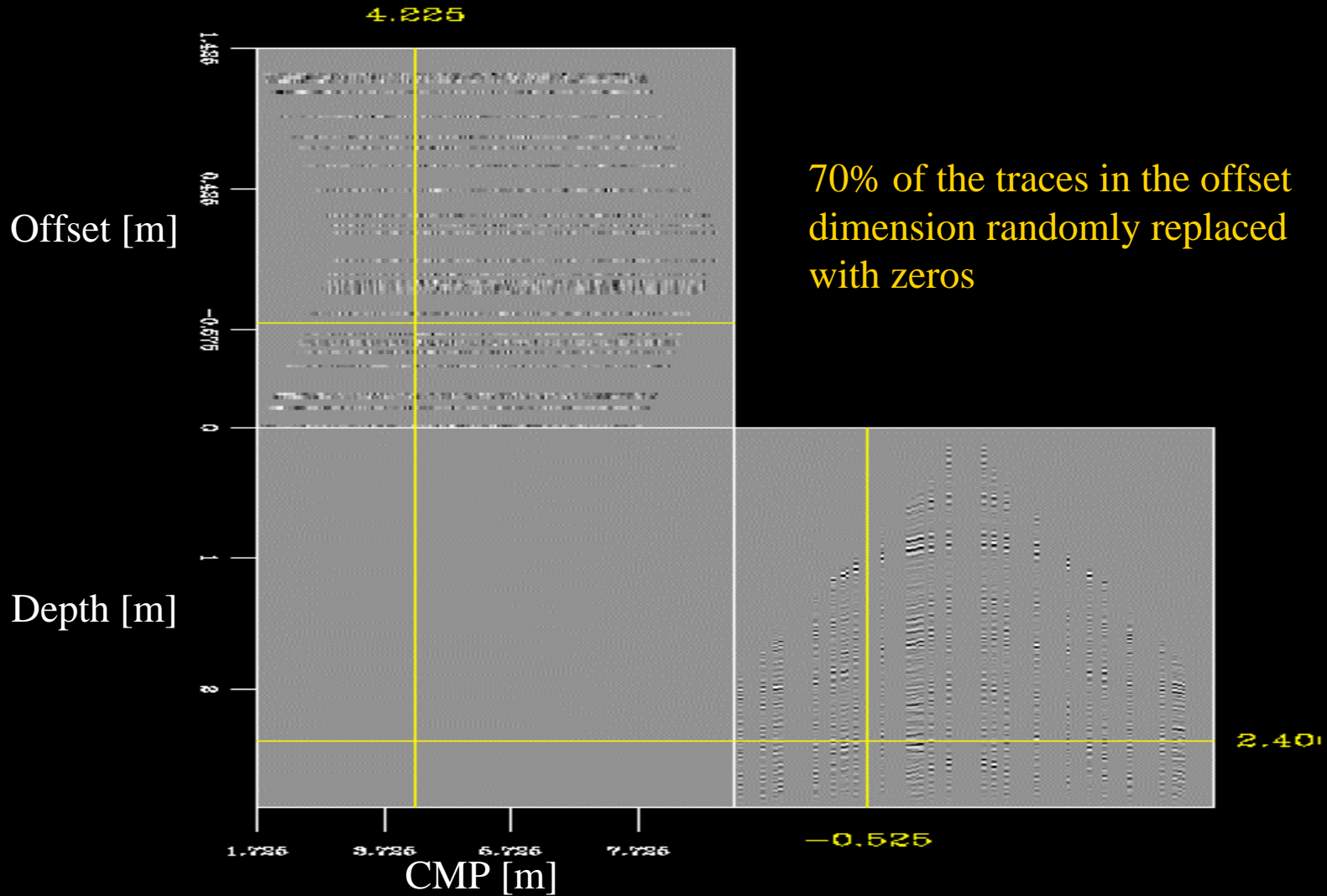
Inversion



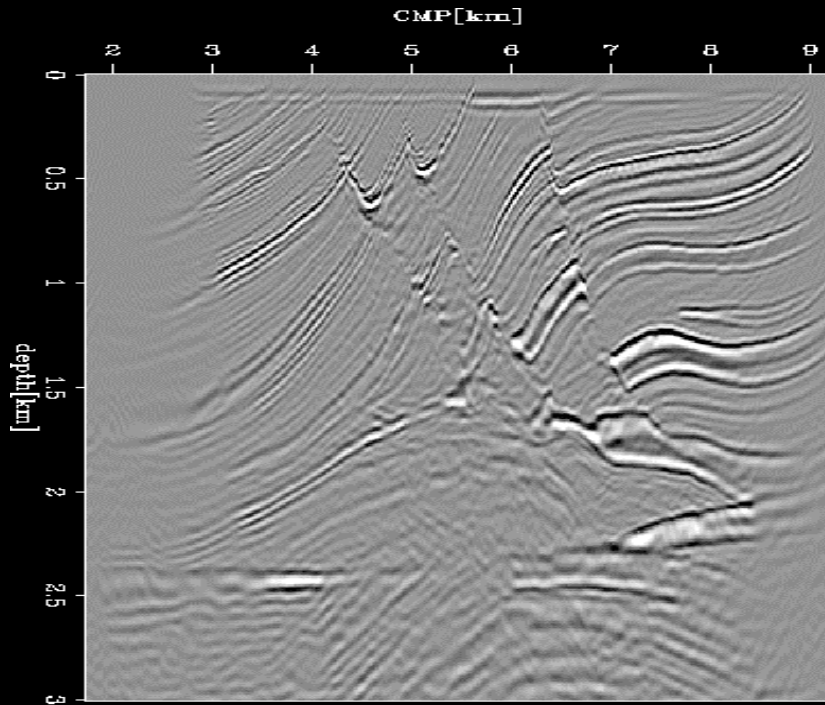
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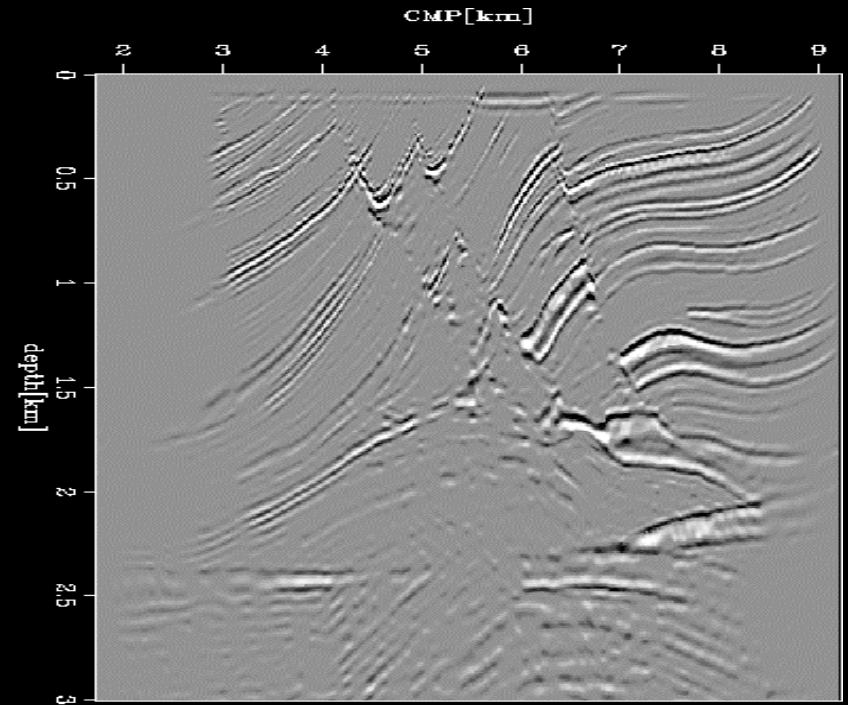


Comparison of images



(a)

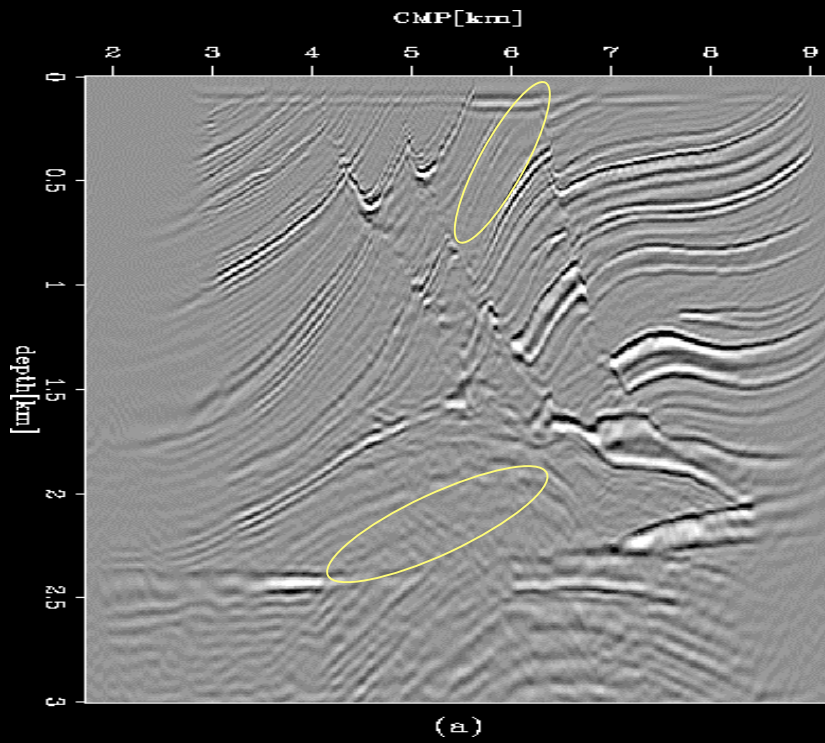
Migration



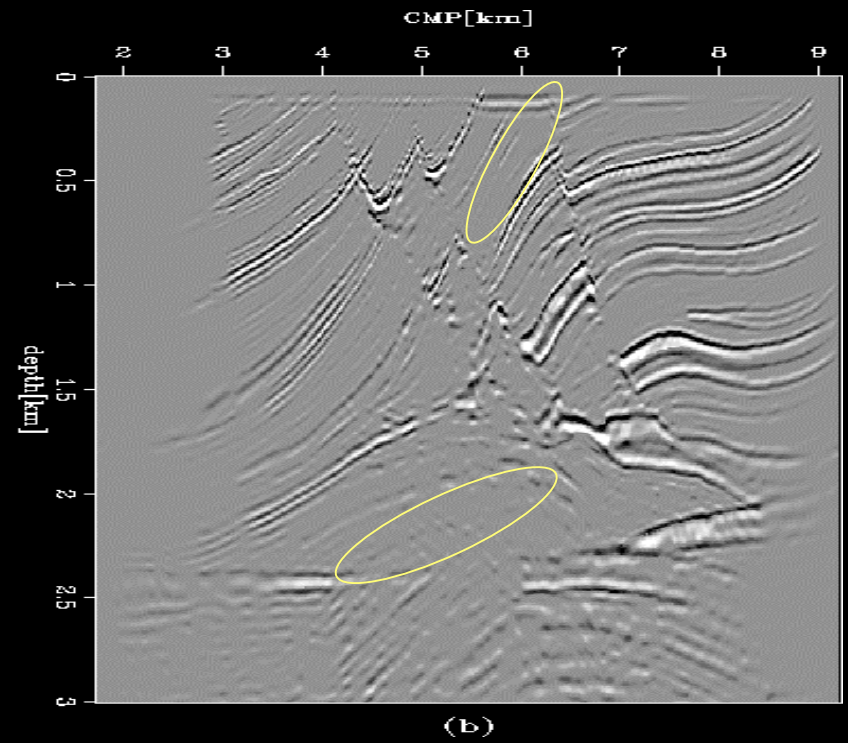
(b)

Inversion

Comparison of images

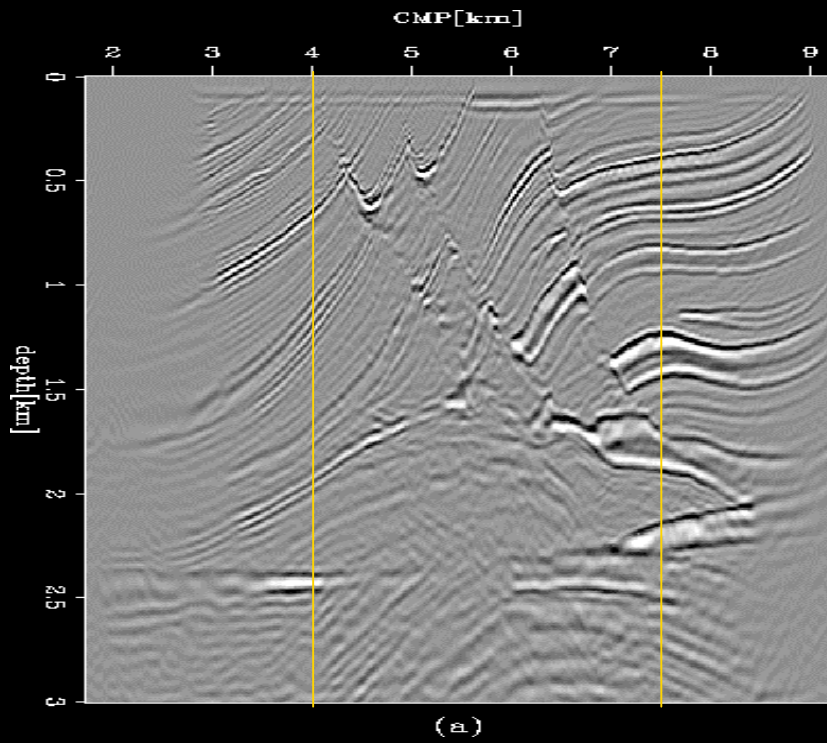


Migration

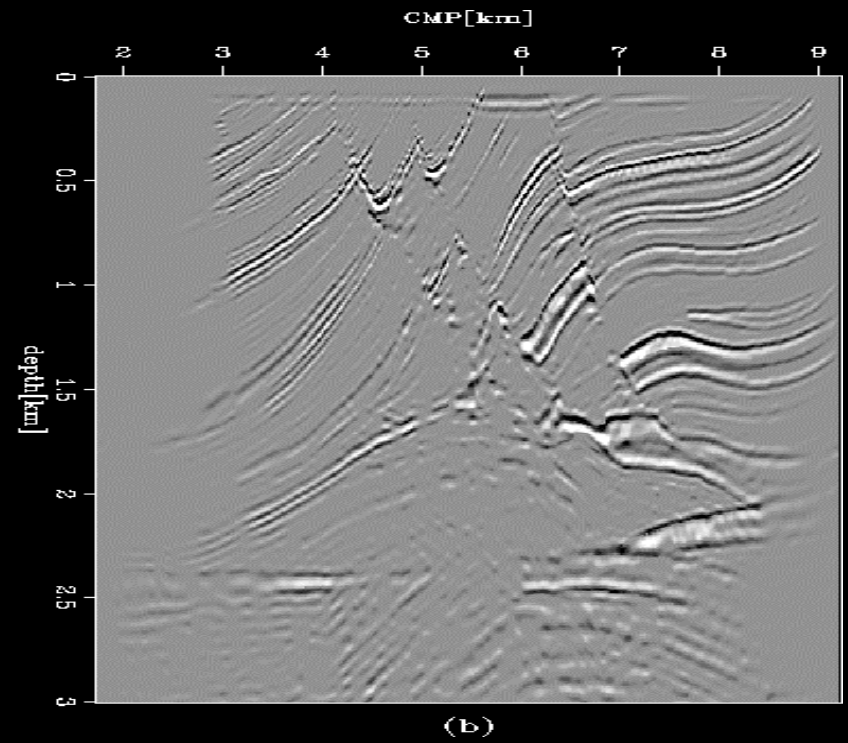


Inversion

Comparison of images

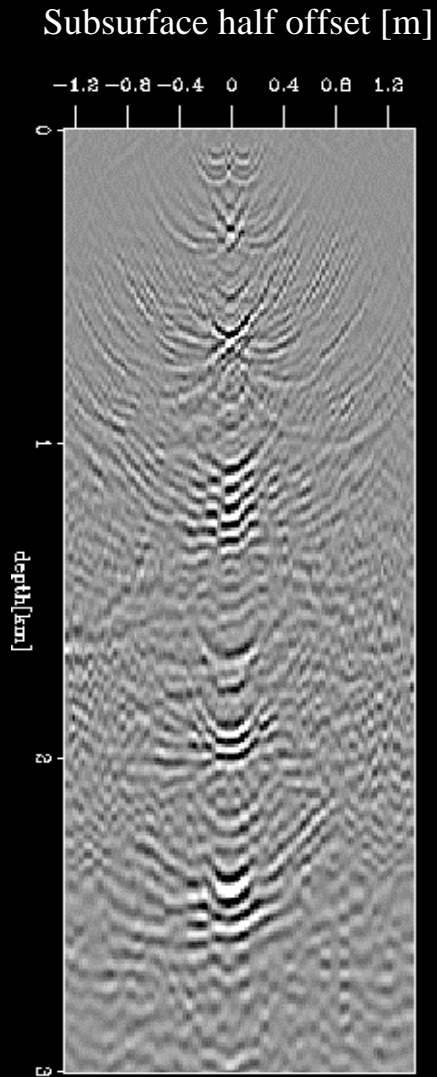


Migration

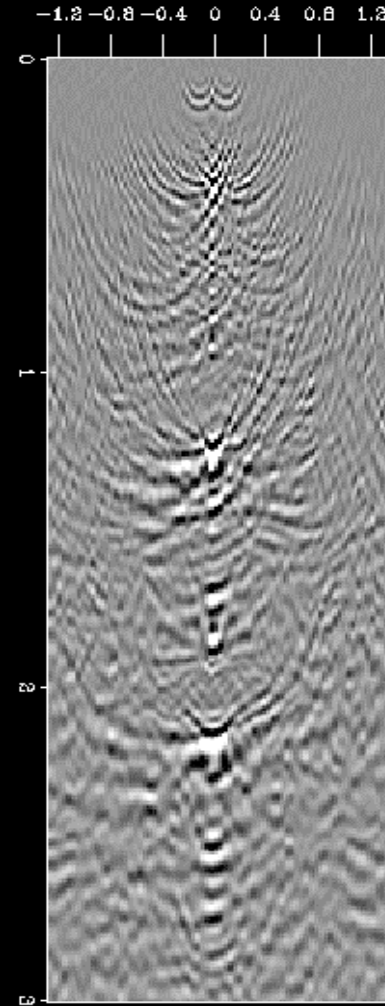


Inversion

Comparison of SODCIGs

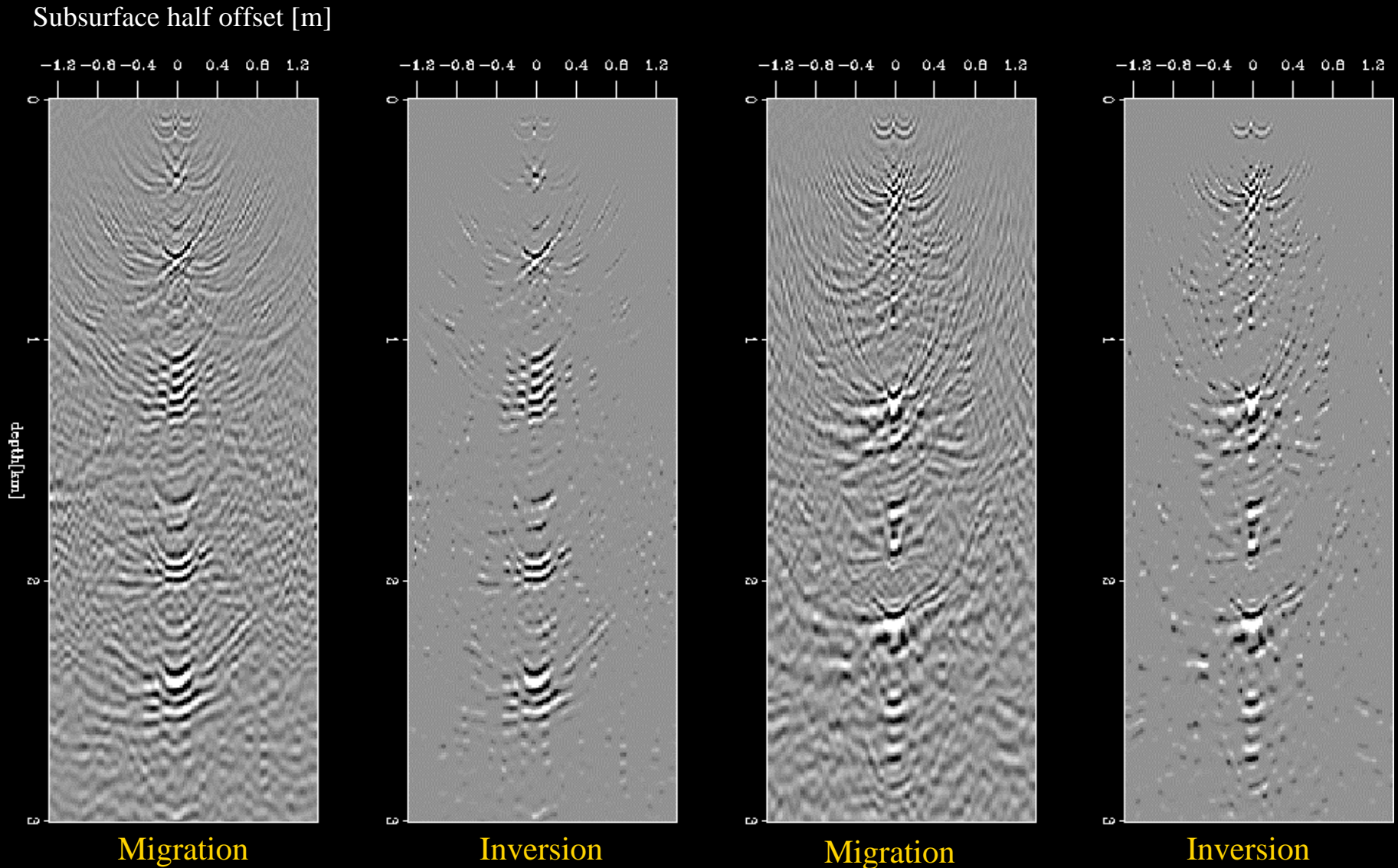


Migration

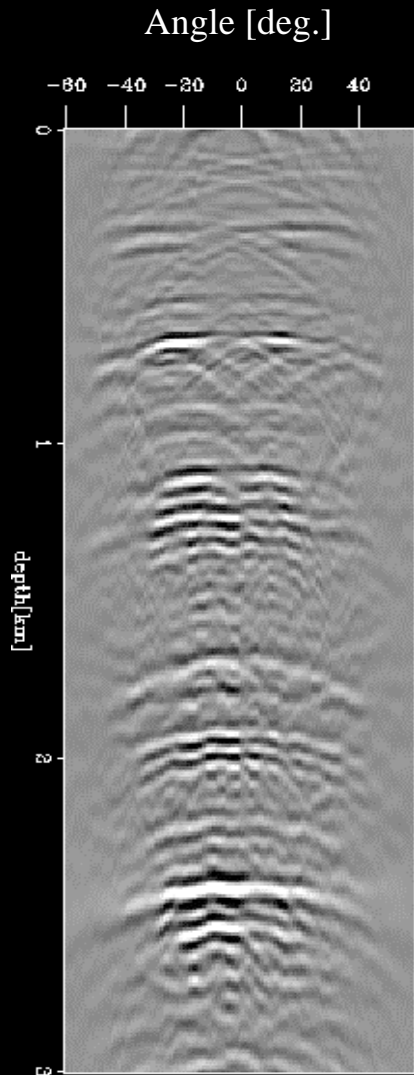


Migration

Comparison of SODCIGs



Comparison of ADCIGs

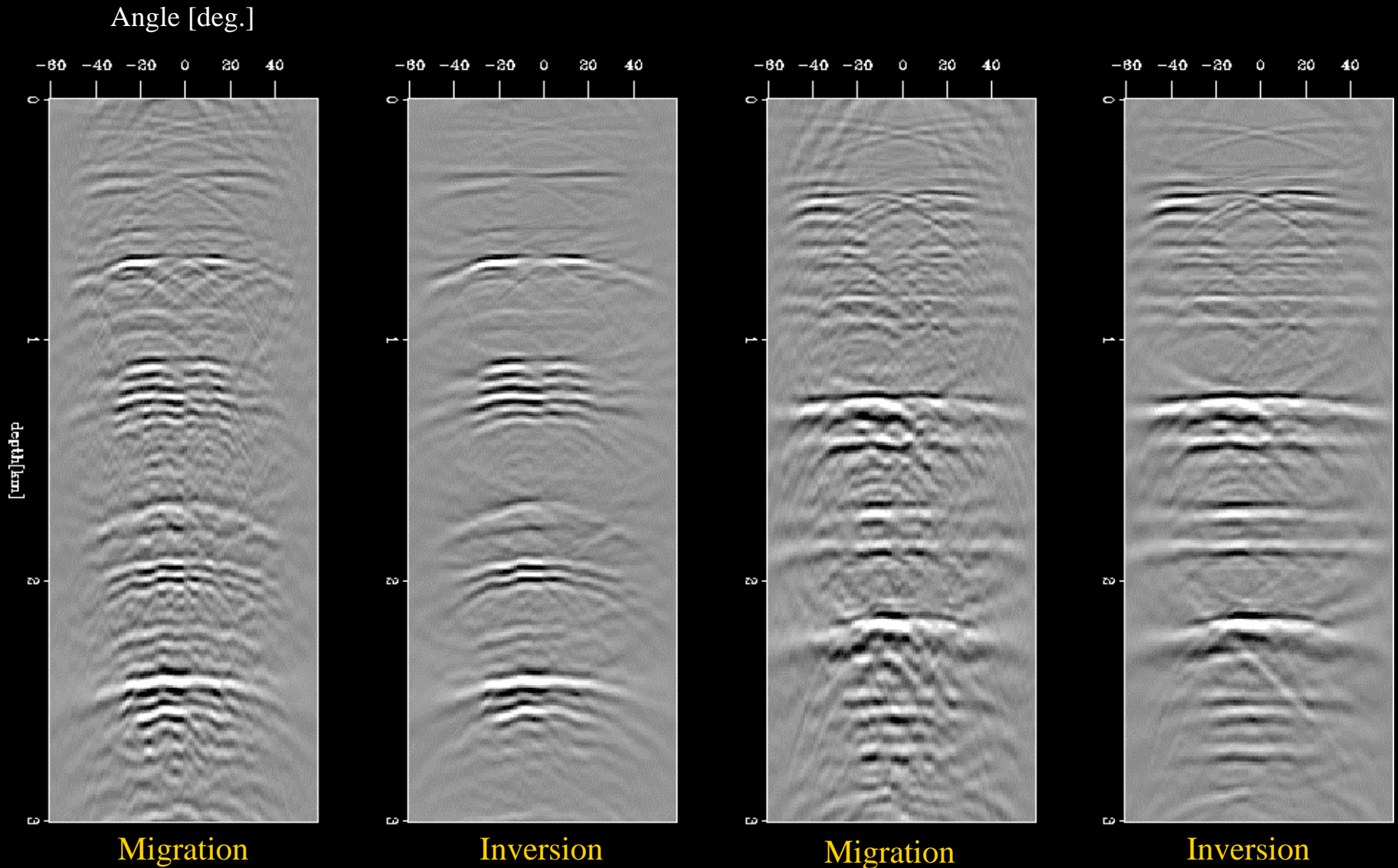


Migration



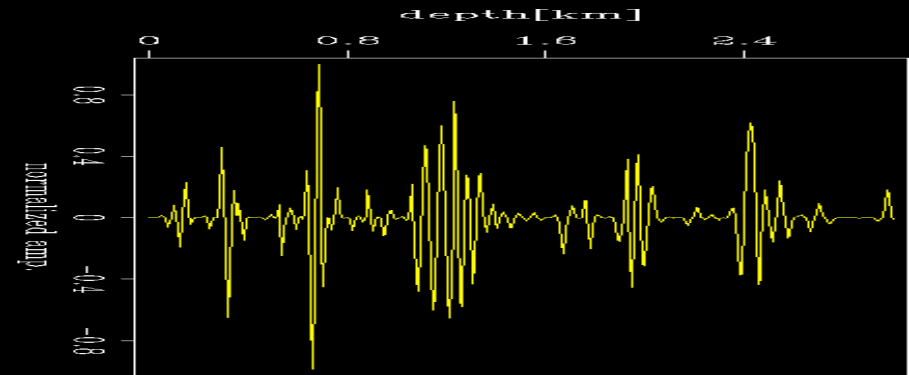
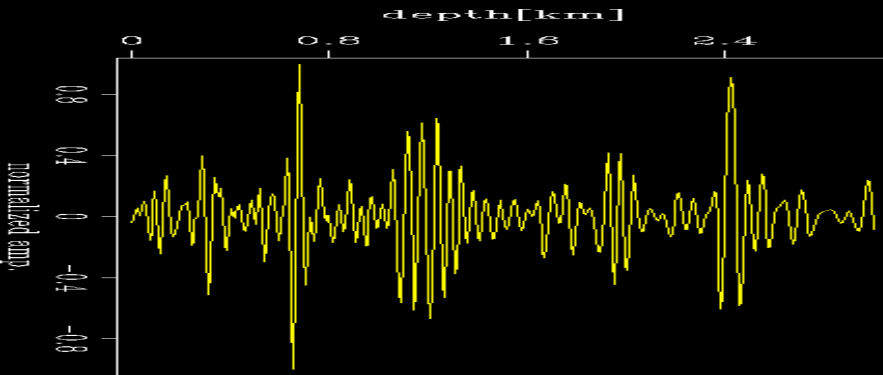
Migration

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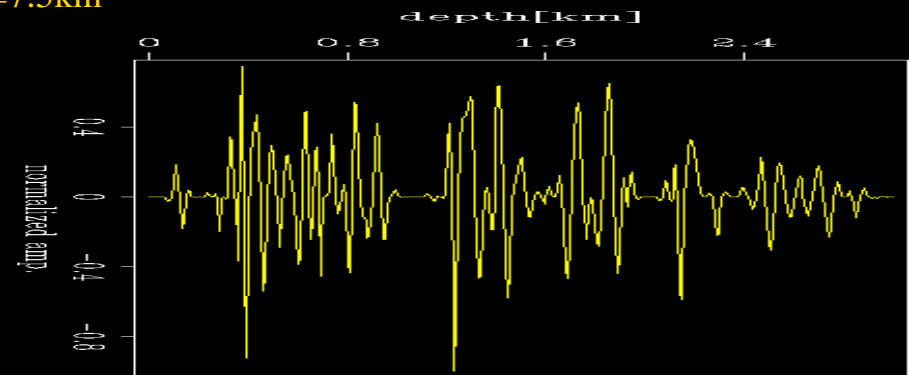
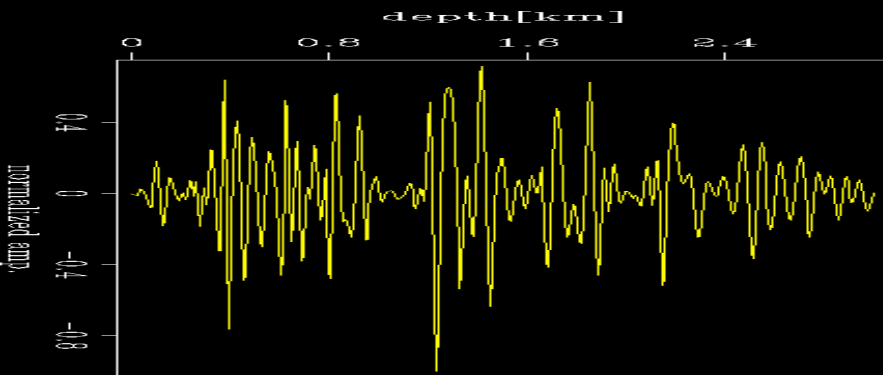


Traces from images

CMP=4km



CMP=7.5km



Migration

Inversion

Conclusions

- Poorly sampled data cause artifacts in the migrated gathers
- The approximate inversion scheme can attenuate those artifacts effectively
- The cost is low compared to the exact inversion scheme
- Hyper-parameters ϵ and σ should be chosen with care to avoid over regularization

Thanks