

Multi-Dimensional Minimum Weighted Norm Interpolation, Survey Regularization and AVA Imaging

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TOPICS

Band-limited signal interpolation

- Minimum norm reconstruction
- Minimum weighed norm reconstruction
- FFT+PCG

Survey Regularization

- 3D DSR Depth Imaging
- 3D DSR AVA Imaging

Future Directions

MOTIVATION

AVA imaging: Lack of amplitude fidelity due to uneven distribution of offsets in CDP bins

Solution:

- Survey Regularization
- LS AVA Imaging
- or, some combination of the above.

TWO PROCESSING SCHEMES

Include sampling considerations at the time of inverting an Earth model (LS Migration)

- LS AVA Migration, H. Kuehl, UofA PhD Thesis, 2002
- 3D AVA Wave equation migration, J. Wang, PhD in progress

Interpolate then invert/migrate

- Pre-stack data regularization, B. Liu, PhD in progress

Survey Regularization

Minimum weighted Norm Interpolation

- Interpolate
- Migrate

Band-Limited Interpolation

1D Problem

Complete data: $\mathbf{x} = [x_1, x_2, x_3, \dots, x_M]^T$

Observations: $\mathbf{y} = [x_{n(1)}, x_{n(2)}, x_{n(3)}, \dots, x_{n(N)}]^T$

Sampling set: $\mathcal{N} = \{n(1), n(2), n(3), \dots, n(N)\}$

Sampling Operator: $\mathbf{y} = \mathbf{T}\mathbf{x}$

$$T_{i,j} = \delta_{n(i),j}$$

$$\mathbf{T}\mathbf{T}^T = \mathbf{I}_N, \quad \mathbf{T}^T\mathbf{T} \neq \mathbf{I}_M$$

Band-Limited Interpolation

Example

$$\begin{pmatrix} x(2) \\ x(3) \\ x(5) \end{pmatrix} = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x(1) \\ x(2) \\ x(3) \\ x(4) \\ x(5) \end{pmatrix}$$

Band-limited Interpolation

Minimum Norm Reconstruction

$$\begin{array}{ll} \text{Minimize} & \|\mathbf{x}\|_{\mathcal{W}}^2 \\ \text{Subject to} & \mathbf{\tilde{T}}\mathbf{x} = \mathbf{y} \end{array}$$

$$\|\mathbf{x}\|_{\mathcal{W}}^2 = \sum_{k \in \mathcal{K}} \frac{X_k^* X_k}{|P_k|^2}$$

$$\mathbf{X} = [X_0, X_1, \dots, X_{M-1}]^T, \quad \mathbf{X} = \mathbf{\tilde{F}}\mathbf{x}$$

Band-limited Interpolation

Minimum Norm Reconstruction

$$\|\mathbf{x}\|_{\mathcal{W}}^2 = \sum_{k \in \mathcal{K}} \frac{X_k^* X_k}{|P_k|^2}$$

- i) $|P_k|^2$ are spectral domain weights with support and shape similar to the spectrum of the signal to interpolate
- ii) $\mathcal{K}$ indicates the region of spectral support of the signal
- iii) $|P_k| \neq 0$ for $k \in \mathcal{K}$

Band-limited Interpolation

Minimum Norm Reconstruction

Define the following diagonal matrices

$$\Lambda_k = \begin{cases} |P_k|^2 & k \in \mathcal{K} \\ 0 & k \notin \mathcal{K} \end{cases}$$

$$\Lambda_k^\dagger = \begin{cases} |P_k|^{-2} & k \in \mathcal{K} \\ 0 & k \notin \mathcal{K} \end{cases}$$

$$\begin{aligned} \|\mathbf{x}\|_{\mathcal{W}}^2 &= \mathbf{x}^H \mathbf{\tilde{F}}^H \mathbf{\tilde{\Lambda}}^\dagger \mathbf{\tilde{F}} \mathbf{x} \\ &= \mathbf{x}^H \mathbf{\tilde{Q}}^\dagger \mathbf{x} \end{aligned}$$

Band-limited Interpolation

Minimum Norm Reconstruction

$$\begin{aligned} ||\mathbf{x}||_{\mathcal{W}}^2 &= \mathbf{x}^H \mathbf{\tilde{F}}^H \mathbf{\tilde{\Lambda}}^\dagger \mathbf{\tilde{F}} \mathbf{x} \\ &= \mathbf{x}^H \mathbf{Q}^\dagger \mathbf{x} \end{aligned}$$

- i) $\mathbf{Q}^\dagger = \mathbf{\tilde{F}}^H \mathbf{\tilde{\Lambda}}^\dagger \mathbf{\tilde{F}}$ is a circulant matrix
- ii) $\mathbf{Q}^\dagger$ is a band-limiting operator, it annihilates any spectral component $k \notin \mathcal{K}$.

Band-limited Interpolation

Minimum Norm Reconstruction

Minimum norm inversion, minimize cost function J :

$$J = \lambda^T (\mathbf{T}\mathbf{x} - \mathbf{y}) + \|\mathbf{x}\|_{\mathcal{W}}^2,$$

$$\hat{\mathbf{x}} = \mathbf{Q}\mathbf{T}^T (\mathbf{T}\mathbf{Q}\mathbf{T}^T)^{-1} \mathbf{y}.$$

i) In general we replace the inverse by $(\mathbf{T}\mathbf{Q}\mathbf{T}^T)^\dagger$

ii) Assume a unit amplitude full-band operator , $\mathbf{Q} = \mathbf{I} \longrightarrow$

$$\hat{\mathbf{x}} = \mathbf{T}^T (\mathbf{T}\mathbf{T}^T)^{-1} \mathbf{y} = \mathbf{T}^T \mathbf{y}.$$

Band-limited interpolation

Minimum norm reconstruction - Example

$$\mathbf{y} = \mathbf{T} \mathbf{x}$$

$$\begin{pmatrix} x(2) \\ x(3) \\ x(5) \end{pmatrix} = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x(1) \\ x(2) \\ x(3) \\ x(4) \\ x(5) \end{pmatrix}$$

$$\hat{\mathbf{x}} = \mathbf{T}^T \mathbf{y} = \begin{pmatrix} 0 \\ x(2) \\ x(3) \\ 0 \\ x(5) \end{pmatrix} \quad \text{Ooohs !!}$$

Band-limited interpolation

Reconstruction of noisy data

Minimize cost function J :

$$J = \|\tilde{\mathbf{T}}\mathbf{x} - \mathbf{y}\|^2 + \rho^2 \|\mathbf{x}\|_{\mathcal{W}}^2$$

Band-limited interpolation

Reconstruction of noisy data

Or, solve the equivalent problem:

$$\begin{pmatrix} \tilde{\mathbf{T}} \\ \rho \tilde{\mathbf{W}} \end{pmatrix} \mathbf{x} \approx \begin{pmatrix} \mathbf{y} \\ \mathbf{0} \end{pmatrix}.$$

$$\tilde{\mathbf{W}} = \tilde{\mathbf{F}}^H \tilde{\mathbf{\Lambda}}^{1/2} \tilde{\mathbf{F}}$$

- i) The augmented matrix of the problem is rank deficient
- ii) Solve it by choosing, among all possible least-squares solutions, the one with minimum Euclidean norm
- iii) SVD or CG

Band-limited interpolation

Reconstruction of noisy data - PCG

Change of variable: $\mathbf{x} = \mathbf{W}\mathbf{z}$

$$\begin{pmatrix} \tilde{\mathbf{T}} \tilde{\mathbf{W}}^\dagger \\ \rho \end{pmatrix} \mathbf{z} \approx \begin{pmatrix} \mathbf{y} \\ \mathbf{0} \end{pmatrix}.$$

- i) The trade-off parameter can be set to $\rho = 0$ and use the number of iterations in the CG method play the role of regularization parameter (Hansen, 1998)
- ii) Solve $\tilde{\mathbf{T}} \tilde{\mathbf{W}}^\dagger \mathbf{z} \approx \mathbf{y}$ and stop the algorithm when a target misfit is achieved

Band-limited interpolation

Reconstruction of noisy data - PCG

Weights can be estimated in an iterative manner using the Modified Periodogram

$$|P_k|^2 = \begin{cases} \sum_{l=-L}^L w_l |X_{k-l}|^2, & k \in \mathcal{K} \\ 0, & k \notin \mathcal{K} \end{cases}$$

or, adopt a non-iterative strategy (Herrmann et al., 2000).

- i) The weights $|P_k|^2$ required to interpolate spatial data at a temporal frequency f can be estimated from the already interpolated data at frequency $f - \Delta f$.
- ii) Helps to reduce alias (mild alias!)

Band-limited interpolation - 2D case

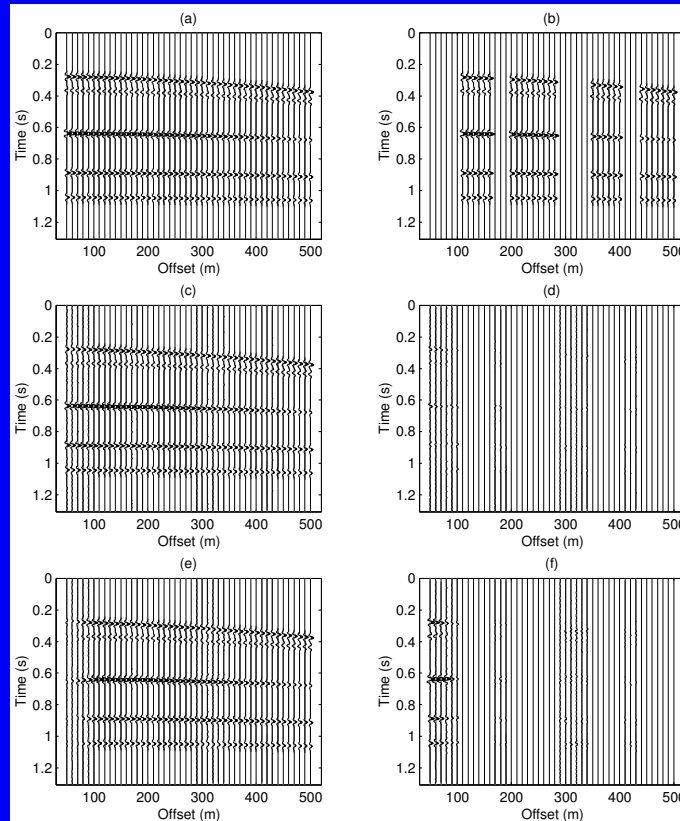
Reconstruction of noisy data - PCG

$$\tilde{\mathbf{T}} \tilde{\mathbf{W}}^\dagger \mathbf{z} \approx \mathbf{y}$$

$$\tilde{\mathbf{W}} = (\tilde{\mathbf{F}}_u \otimes \tilde{\mathbf{F}}_v)^H \tilde{\mathbf{\Lambda}}^{1/2} (\tilde{\mathbf{F}}_u \otimes \tilde{\mathbf{F}}_v).$$

- i) The Kronecker tensor product is not needed
- ii) Inner products required by PCG are computed in the flight
- iii) Generalization to ND is straightforward

EXAMPLE 1 - MWNI vs MNI

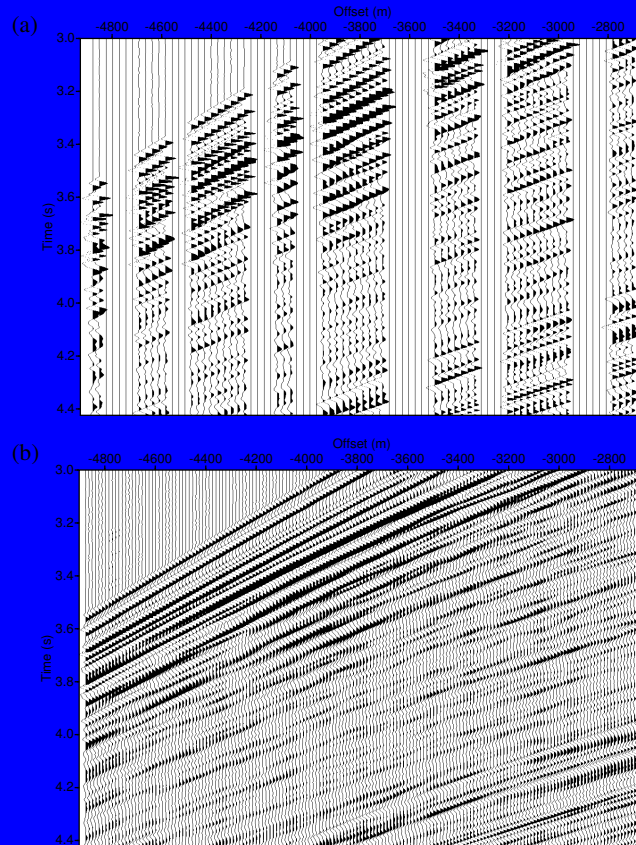


a) True, b) Decimated, c) MWNI reconstruction, d) MWNI error panel, e) MNI reconstruction, and f) MNI error panel.

EXAMPLE 2 - Gulf of Mexico CSG

- MWNI is used to recover missing data (gaps) and to interpolate ($\Delta h_{new} = 1/2\Delta h_{old}$)

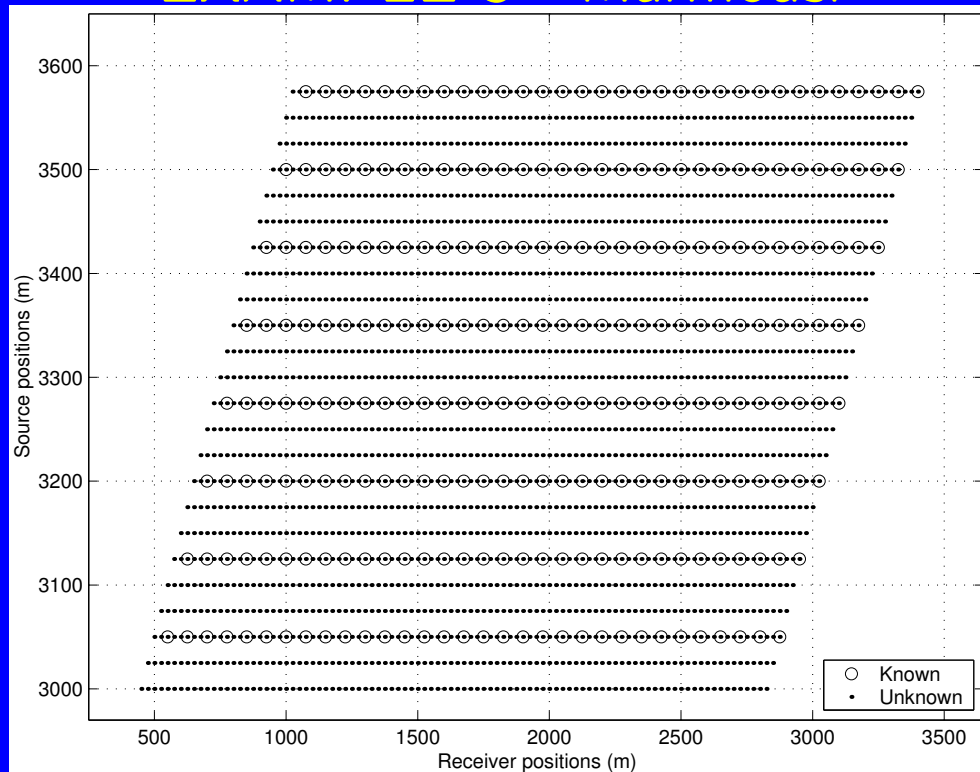
EXAMPLE 2 - Gulf of Mexico CSG



EXAMPLE 3 - Marmousi

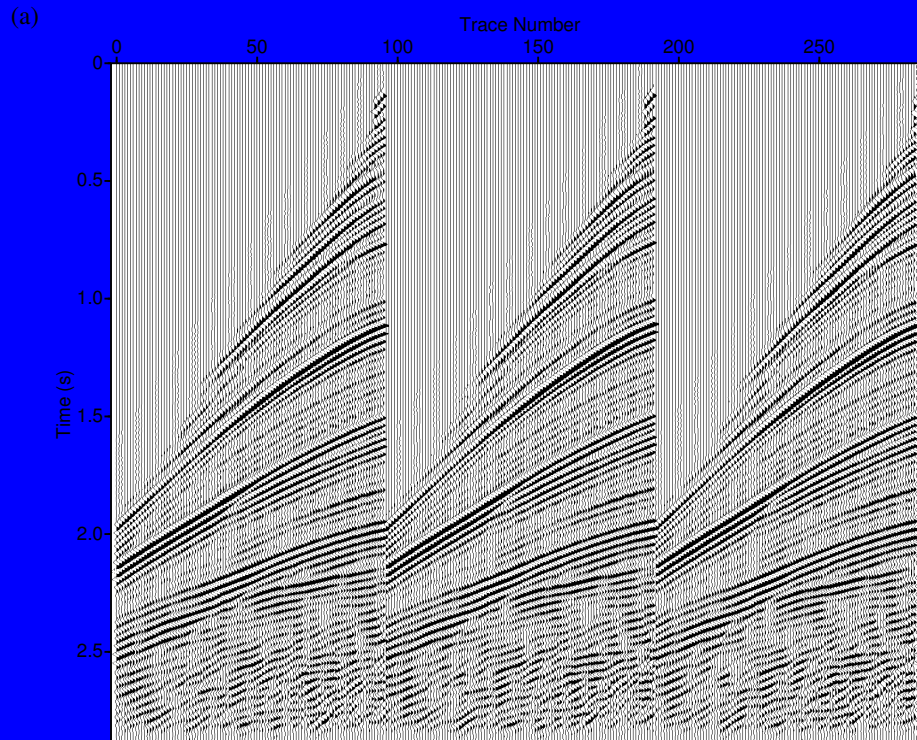
- 1 - Data are decimated in both receiver/shot
- 2 - MWNI is used to recover "decimated" positions

EXAMPLE 3 - Marmousi



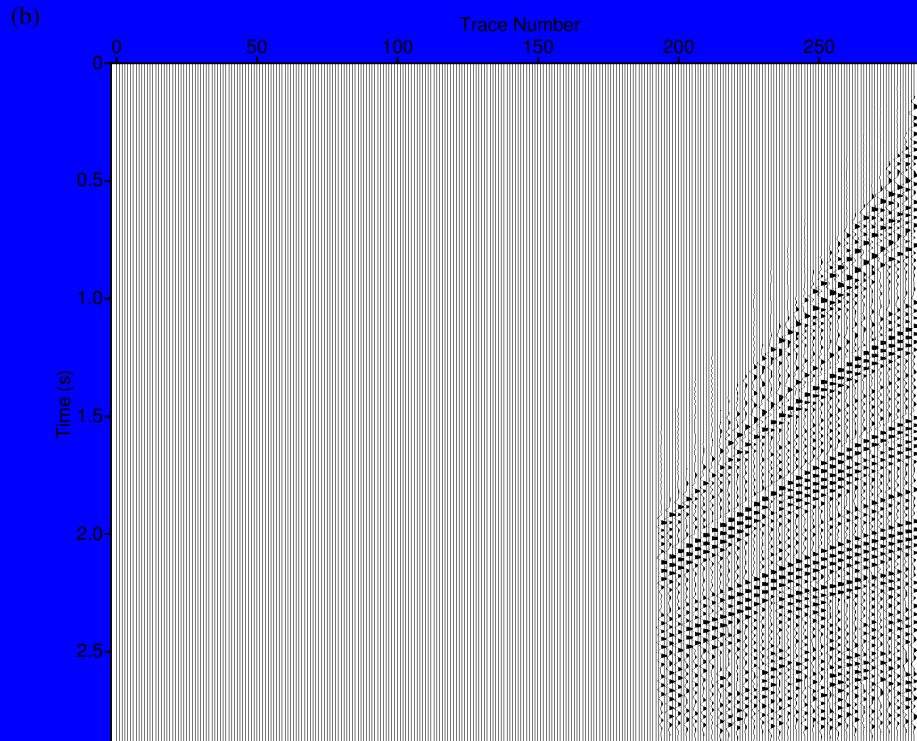
Data used in the numerical experiment

EXAMPLE 3 - Marmousi



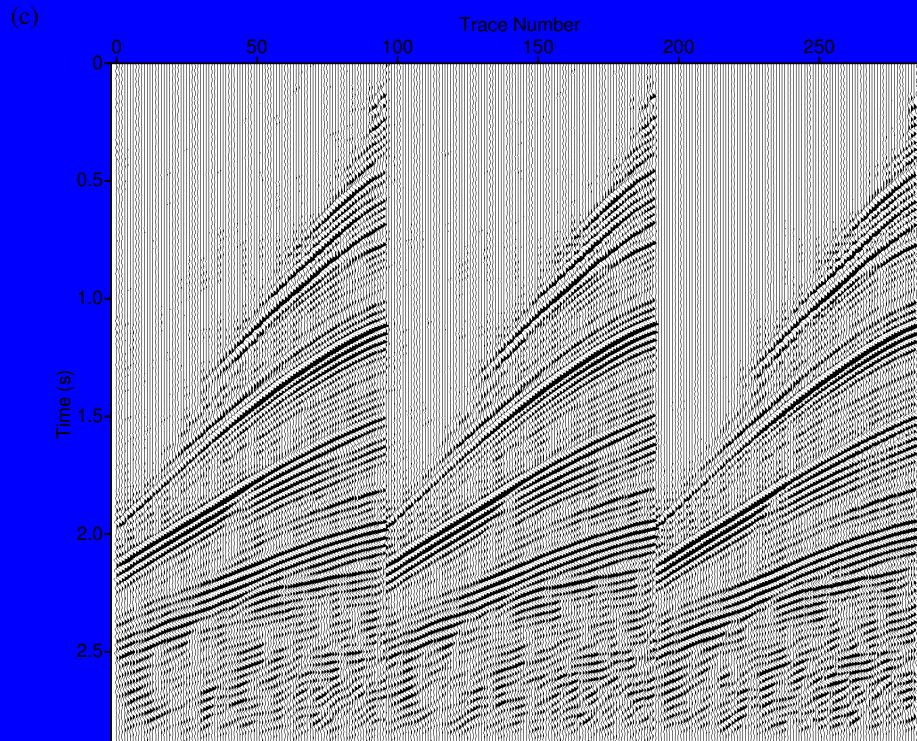
Shots at source positions 3075, 3100, 3125 *m.*

EXAMPLE 3 - Marmousi



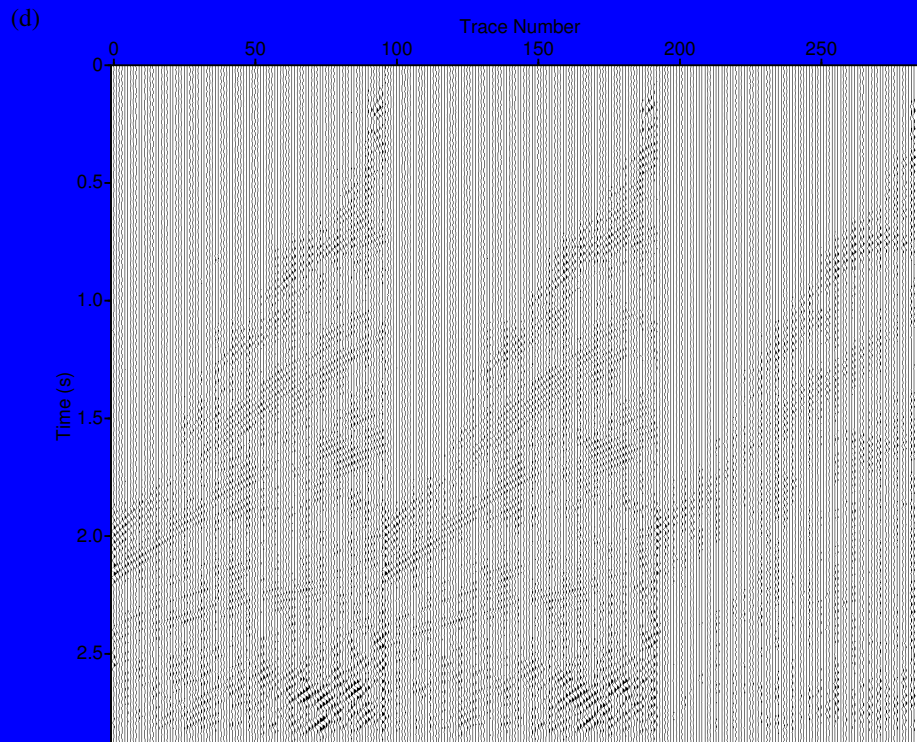
Shots at source position 3075, 3100, 3125 *m* after decimation.

EXAMPLE 3 - Marmousi



MWNI Reconstuction, source position 3075,3100,3125 m .

EXAMPLE 3 - Marmousi

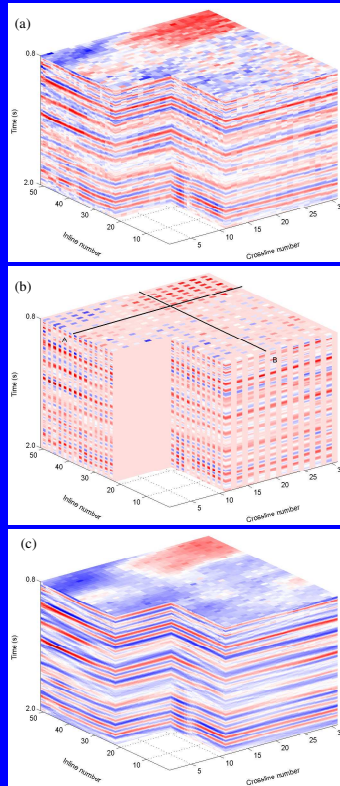


Error panel: Reconstructed shots minus original shots.

EXAMPLE 4 - 3D WCB

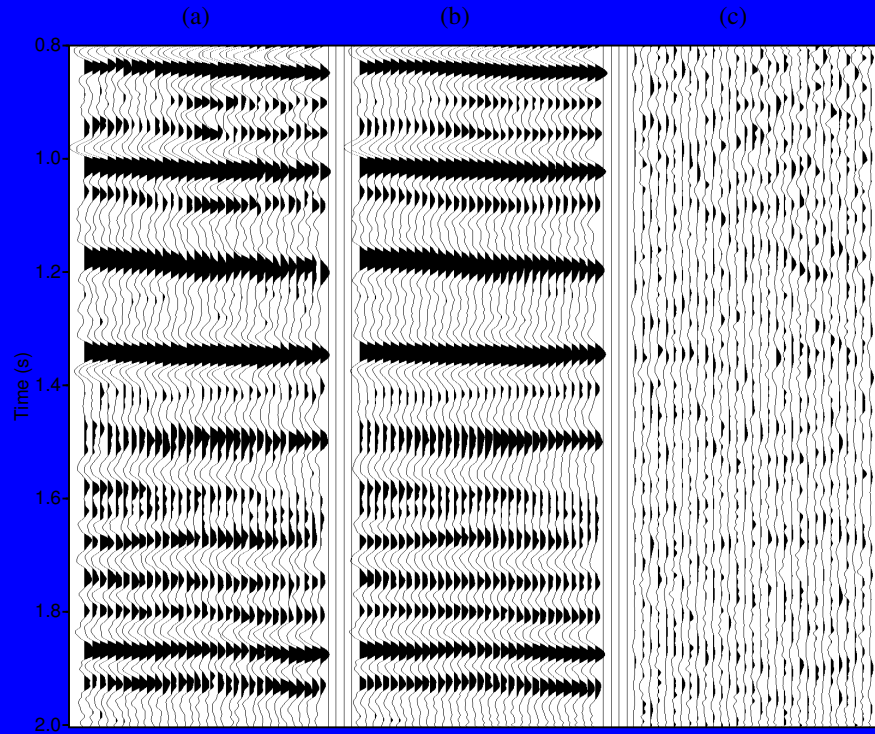
Post stack Interpolation and SNR Enhancement

EXAMPLE 4 - 3D WCB



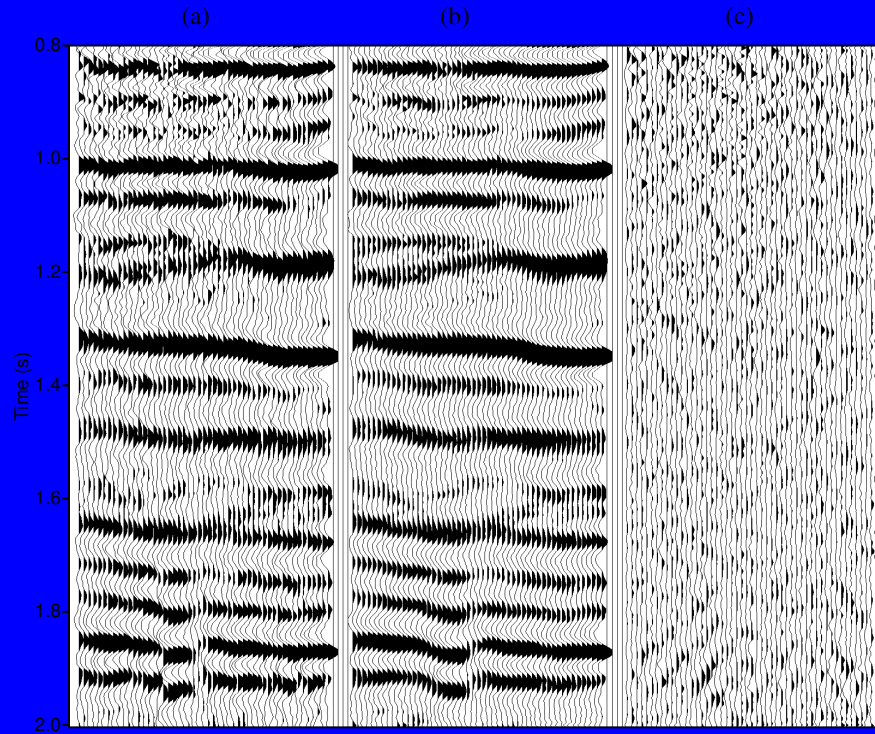
a) Original Post-stack cube. b) Decimated cube. c)
reconstructed cube with MWNI.

EXAMPLE 4 - 3D WCB



a) Original. b) Reconstructed with MWNI. c) error.

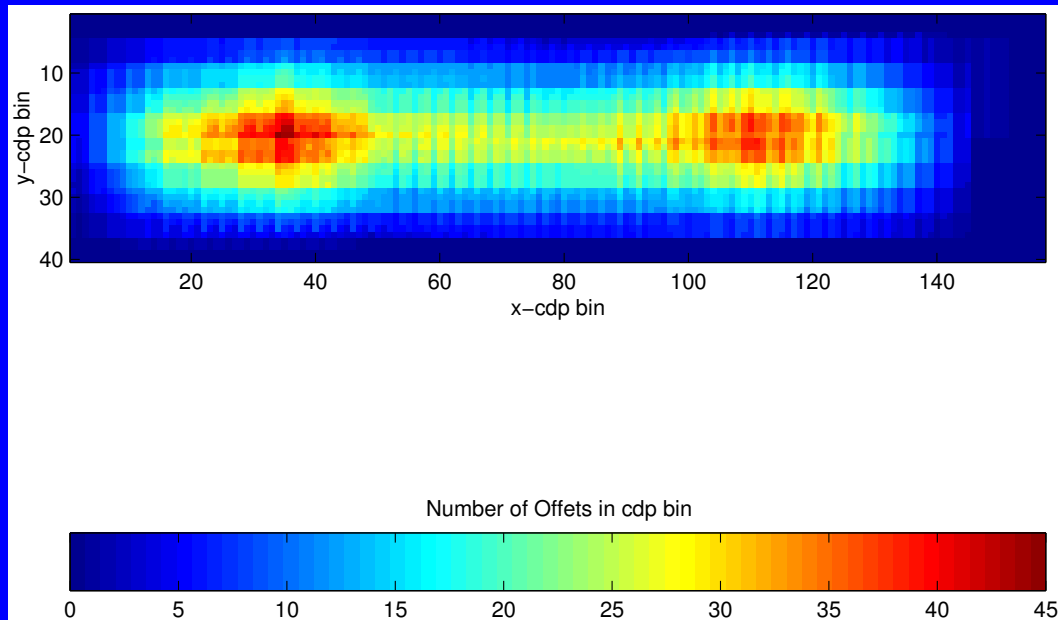
EXAMPLE 4 - 3D WCB



a) Original. b) Reconstructed with MWNI. c) error.

EXAMPLE 5 - WCB Sparse 3D (Erskine) Veritas

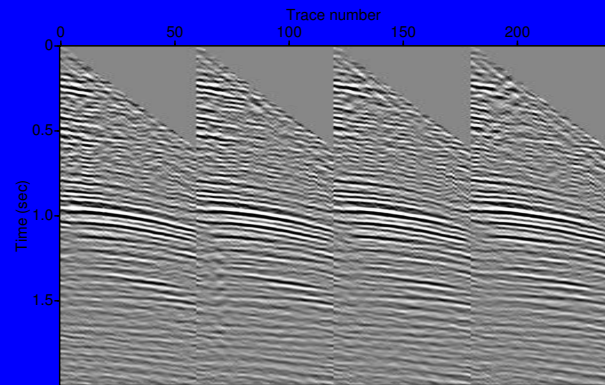
EXAMPLE 5 - WCB Sparse 3D (Erskine)



Interpolation to a regular x_m, y_m, h_x grid

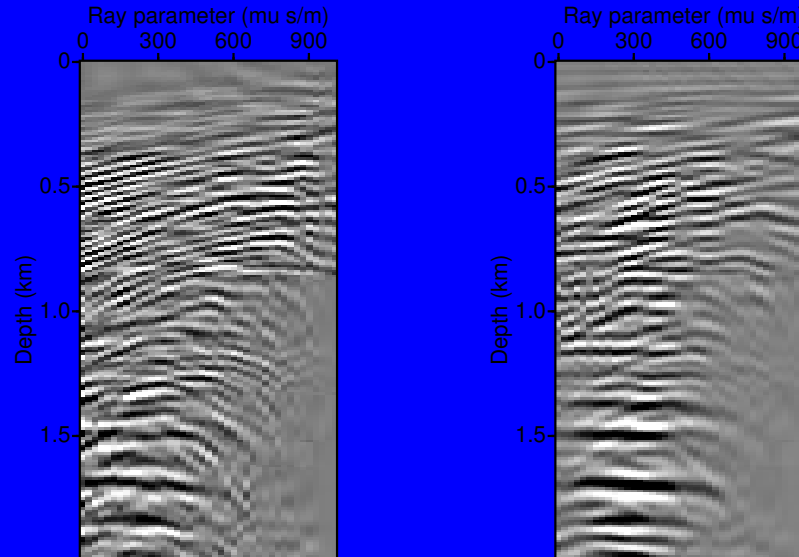
is required before Common Azimuth AVP Wave Equation Migration
(Kuehl and Sacchi, SEG2001; Biondi et. al, EAGE2002)

EXAMPLE 5 - WCB Sparse 3D (Erskine)



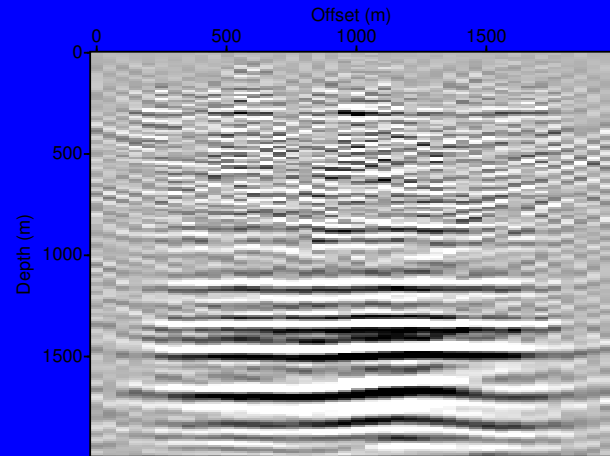
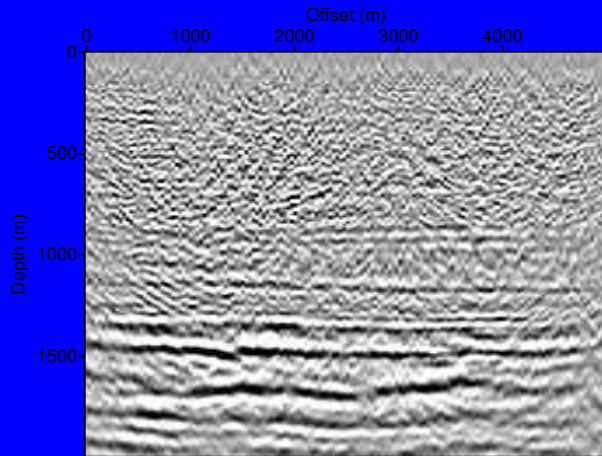
Inline 6, Crossline 15 to 18
Left: Original. Right: After MWNI

EXAMPLE 5 - WCB Sparse 3D (Erskine)



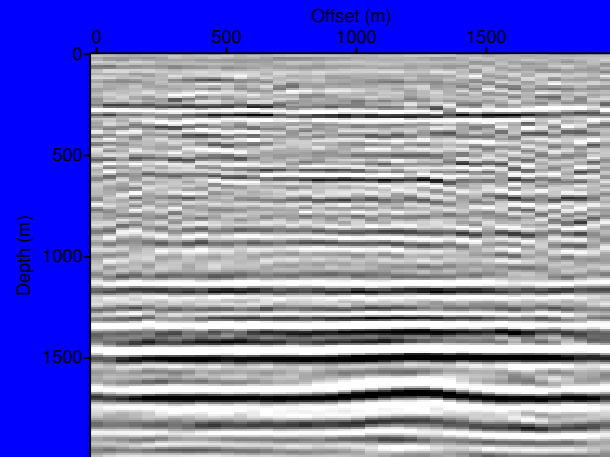
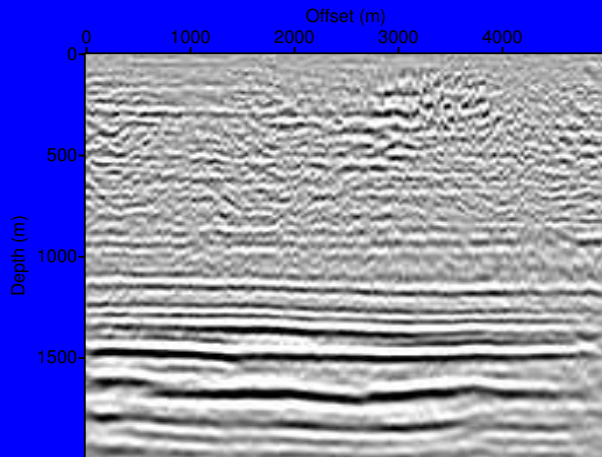
CIG (AVP) gathers. Left: No interpolation. Right: After MWNI

EXAMPLE 5 - WCB Sparse 3D (Erskine)



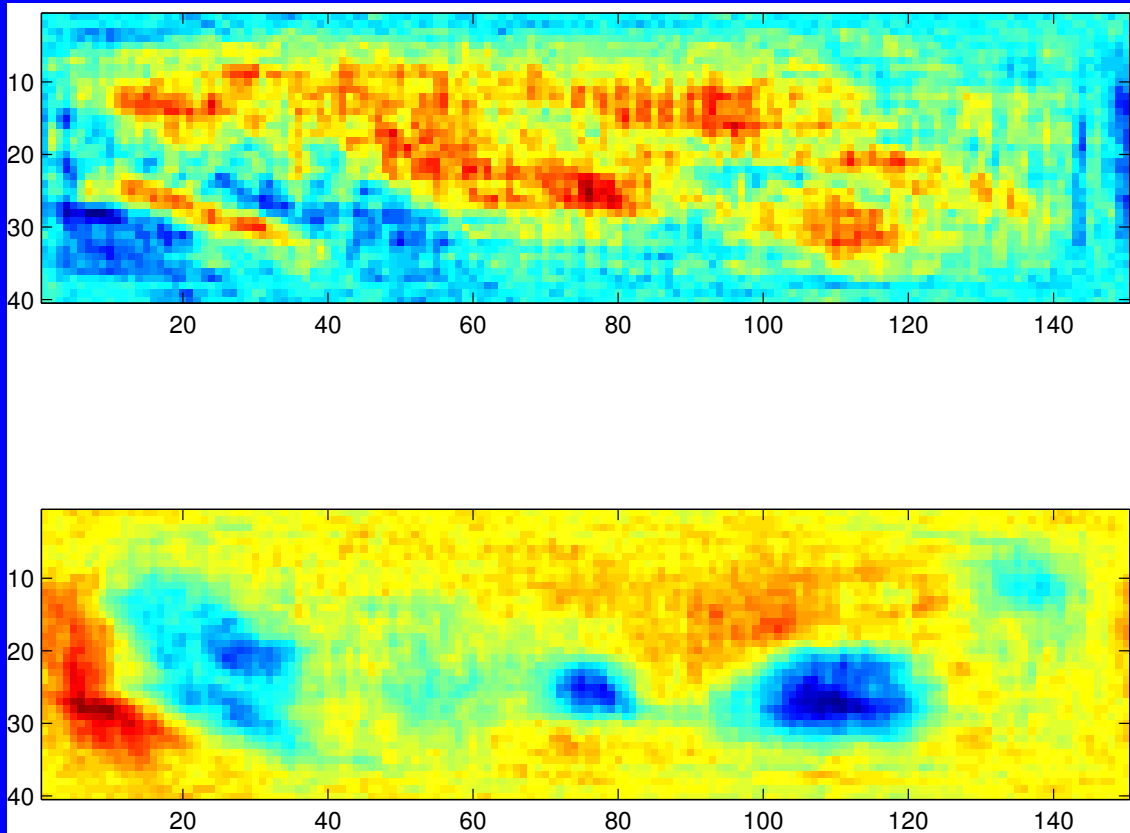
Migration [NO interpolation] Left: inline 36. Right: xline 71

EXAMPLE 5 - WCB Sparse 3D (Erskine)



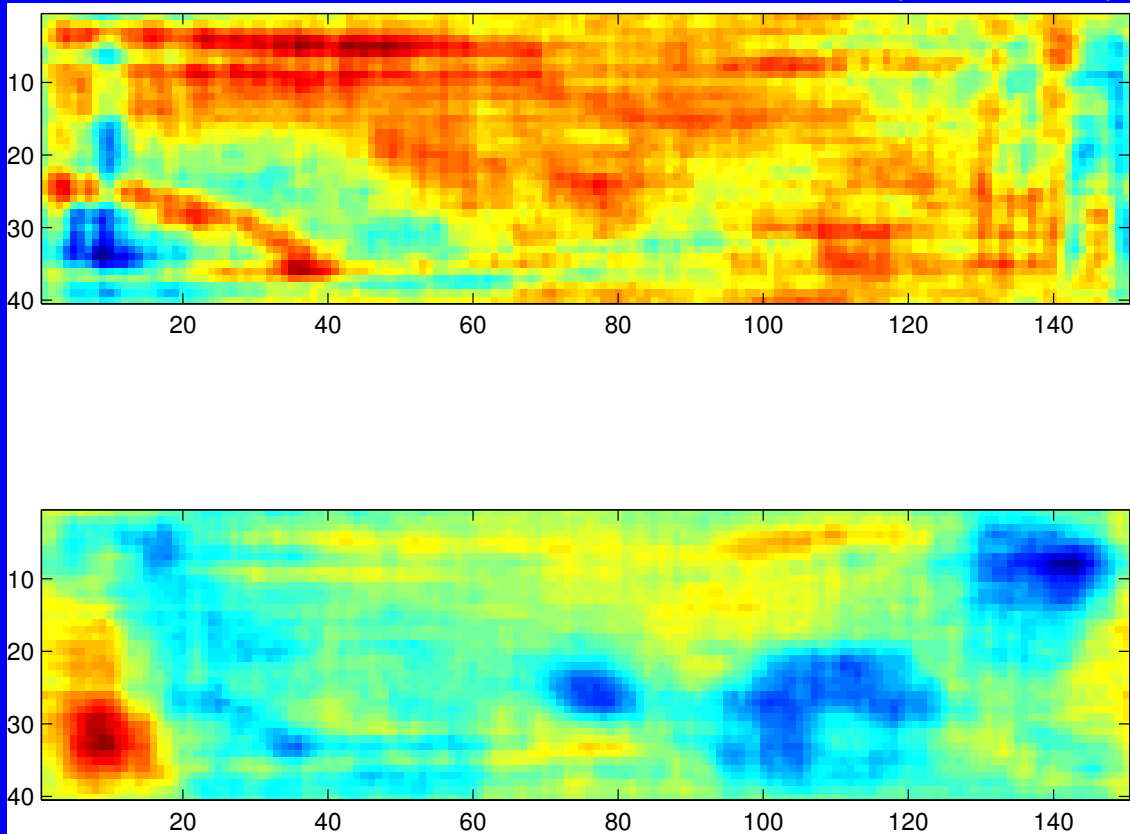
Migration after MWNI. Left: inline 36. Right: xline 71

EXAMPLE 5 - WCB Sparse 3D (Erskine)



Depth slices [NO interpolation] Top: $z = 1420\text{ m}$. Bottom: $z = 1620\text{ m}$

EXAMPLE 5 - WCB Sparse 3D (Erskine)



Depth slices after interpolation. Top: $z = 1420\text{ m}$. Bottom: $z = 1620\text{ m}$

EXAMPLE 5 - WCB Sparse 3D (Erskine) All AVP Gathers

www-geo.phys.ualberta.ca/~sacchi/movies.html

Summary

- i) MWNI: Efficient and simple (PCG and FFT)
- ii) Better than MNI at the time of handling large gaps
- iii) Simple to implement in any domain

Near future work:

- i) Compare with AVA gathers obtained via LS migration
- ii) Continue with amplitude fidelity studies (Kuehl and Sacchi, Geophysics 03)
- iii) Alternatives (Radon, Azimuth Moveout, etc)

References [Interpolation]

Cabrera S.D. and Parks T.W., 1991, Extrapolation and spectrum estimation with iterative weighted norm modification: IEEE Trans. Signal Processing, **39**, 842-850.

Duijndanm A.J.W., Schonewille M., and Hindriks K., 1999, Reconstruction of seismic signals, irregularly sampled along on spatial coordinate: Geophysics, **64**, 524-538.

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