Wave-equation MVA using partial stack-power-maximization

Chevron

Human Energy[®]

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Outline

- Wave equation MVA (WEMVA) background
 - Common Image Gather in angle and offset domain
 - WEMVA workflow
- Partial image-stack power objective function

WEMVA characteristics

- Wave-equation migration velocity analysis
 - Is a reflection tomography method
 - Optimizes objective function defined in image domain
 Common image gathers

• Uses wave-equation operator to compute images & velocity updates (wave path **not** ray path).

Common-image gather in reflection angle domain

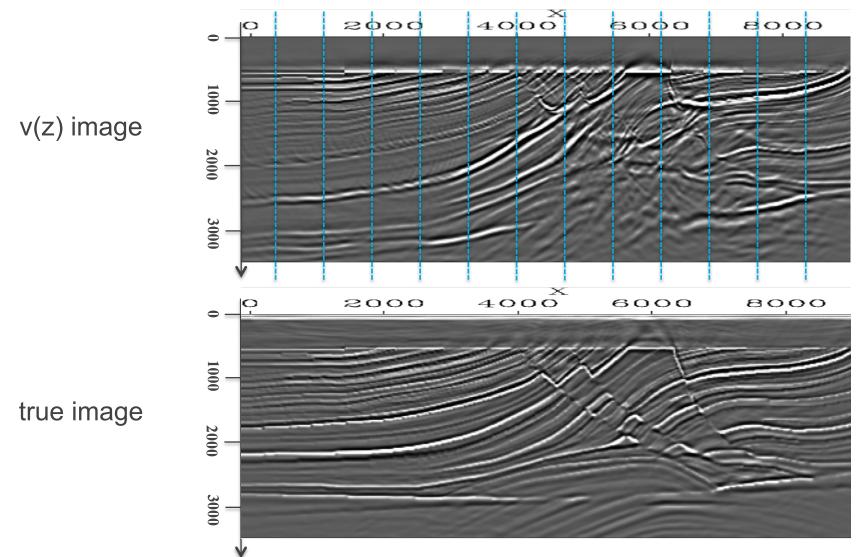
- Imaging the same reflector with different incident angles (same in reflection ray-tomography)
- In ideal case, the more correct the velocity model, the more the gathers are flat
- More expensive to compute using wave-equation

Common-image gather in subsurface offset domain

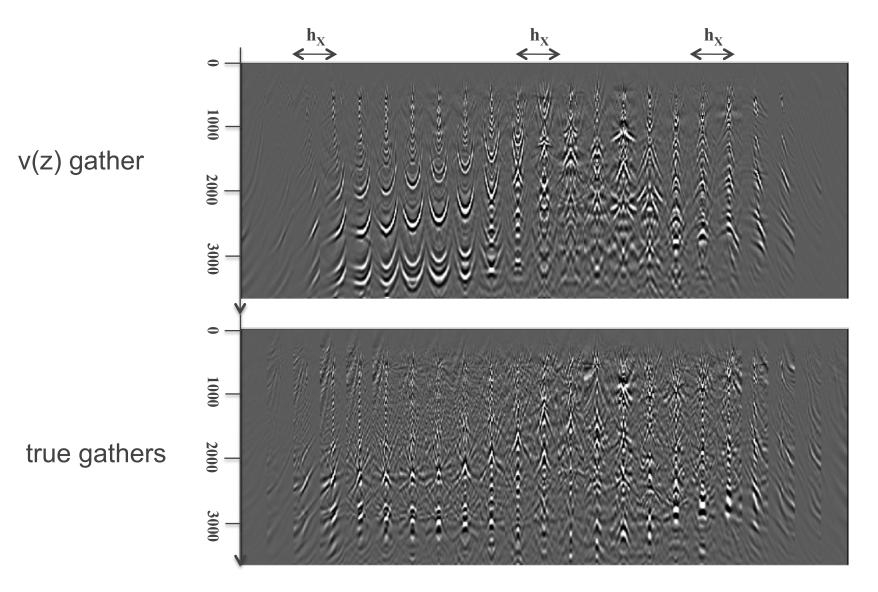
- Different from surface offset-gathers used frequently in Kirchhoff migration
- In ideal case, the more correct the velocity model, the gathers are more **focused on h=0** (rather than being flat)
- Computationally easy to implement

$$I(z,x,h) = \sum_{t} U(z,x+h,t)D(z,x-h,t)$$

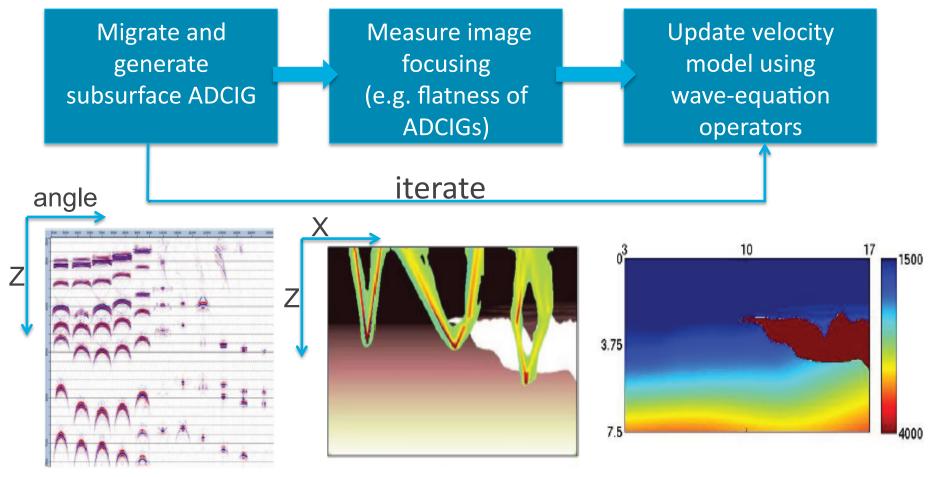
Zero-subsurface offset domain



Subsurface offset gathers



General WEMVA flow





WEMVA objective functions

- Stack-power-maximization (SPM) $\max_{s} J(s) \text{ with } J(s) = \sum_{z,x} \left[\sum_{\gamma} I(z,x,\gamma;s) \right]^{2}$
- Differential semblance optimization (DSO)

$$\min_{s} J(s) \text{ with } J(s) = \sum_{z,x} \sum_{\gamma} \left[\frac{\partial I(z,x,\gamma;s)}{\partial \gamma} \right]^{2}$$

z, x: spatial coordinate, γ : refl ection angle s: slowness fi el

WEMVA objective functions

- Stack-power-maximization (SPM) (Gratacous,2005) $\max_{s} J(s) \text{ with } J(s) = \sum_{z,x} \left[\sum_{\gamma} I(z, x, \gamma, s) \right]^{2} \text{ Global convergence}$ problems
- Differential semblance optimization (DSO),
 (Shen&Symes, 2008)
 Sensitive to image

$$\min_{s} J(s) \text{ with } J(s) = \sum_{z,x} \sum_{\gamma} \left[\frac{\partial I(z,x,\gamma;s)}{\partial \gamma} \right]^2 \qquad \text{amplitudes} \\ \bullet \text{ Sensitive to CIGs artifacts} \\ \bullet \text{ Problems in 3D}$$

z, x: spatial coordinate, γ : reflection angle, s: slowness field

Outline

- Wave equation MVA background
- Partial Image-stack power objective function

Partial stack power maximization

Existing stack power maximization

$$J = \|\sum_{\gamma} I(z, x, \gamma)\|_2^2$$

Partial stack power maximization

Existing stack power maximization

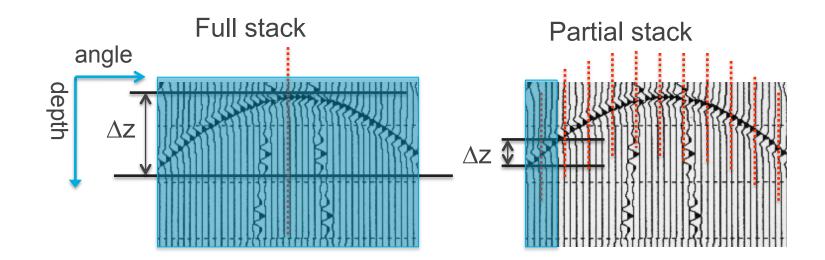
$$J = \|\sum_{\gamma} I(z, x, \gamma)\|_2^2$$

Using partial stack

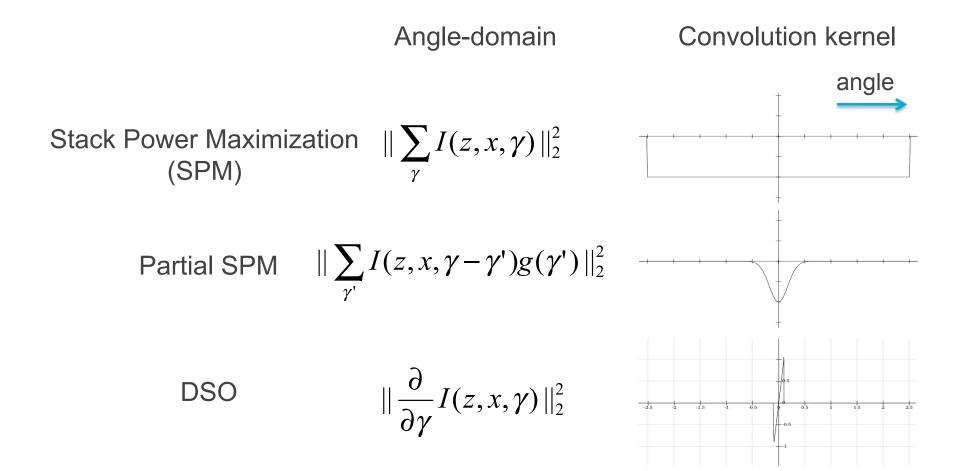
$$J = \left\|\sum_{\gamma'} I(z, x, \gamma - \gamma') g(\gamma')\right\|_{2}^{2}$$

- $-g(\gamma')$ is a low-pass filtering kernel
 - Box function / triangular function / Gaussian function
- Properties of partial stack
 - More robust against cycle-skipping problem as in previous stack-power maximization method
 - Is a generalization of the previous method

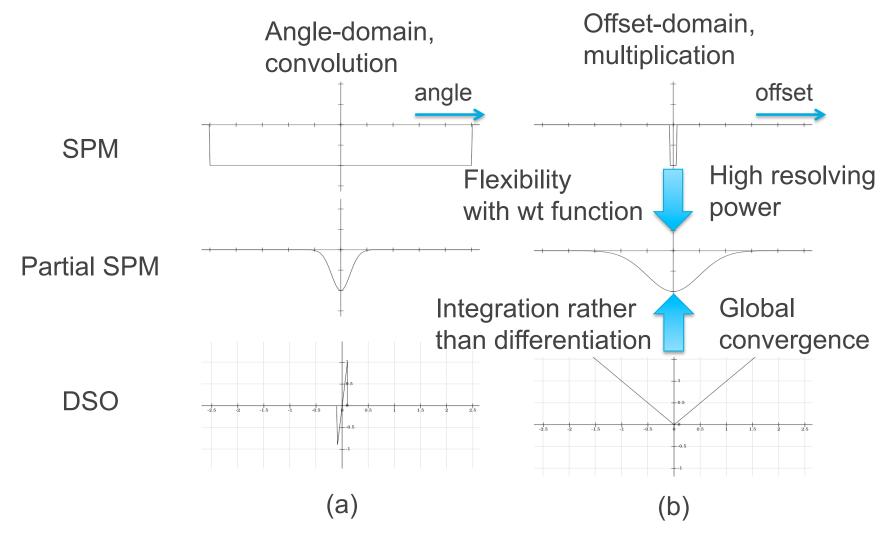
Partial stacking avoids cycle-skipping



WEMVA objective functions in angle domain



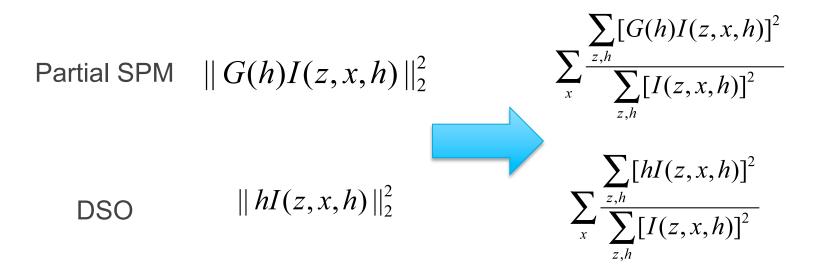
Comparison of WEMVA objective functions (graphic)



Comparison of WEMVA objective functions (equation)

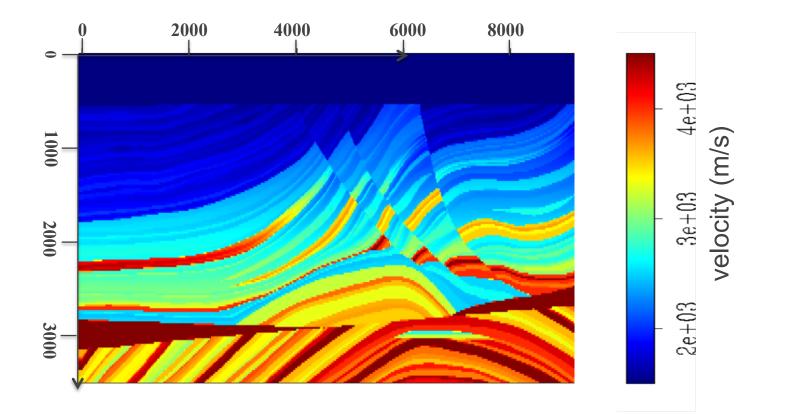
Angle-domainOffset-domainStack Power Maximization
$$\|\sum_{\gamma} I(z, x, \gamma)\|_2^2$$
 $\|I(z, x, h = 0)\|_2^2$ (SPM)FlexibilityHigh resolving
powerPartial SPM $\|\sum_{\gamma'} I(z, x, \gamma - \gamma')g(\gamma')\|_2^2$ $\|G(h)I(z, x, h)\|_2^2$ Integration rather
than differentiationGlobal
convergenceDSO $\|\frac{\partial}{\partial \gamma} I(z, x, \gamma)\|_2^2$ $\|hI(z, x, h)\|_2^2$

Energy Normalized WEMVA objective functions

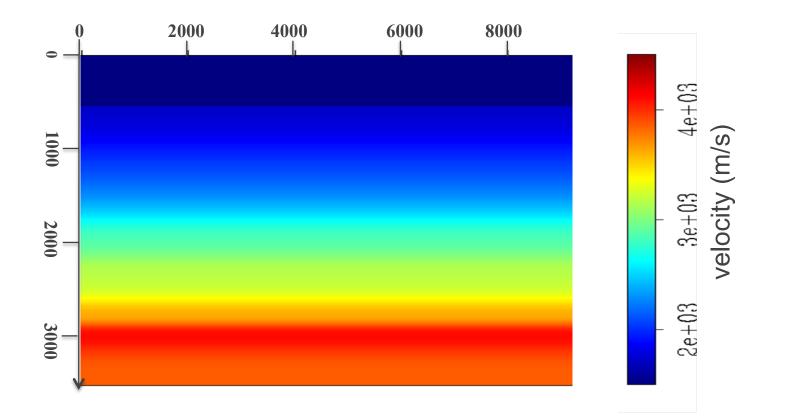


From Tang, Ph.D Thesis, 2011

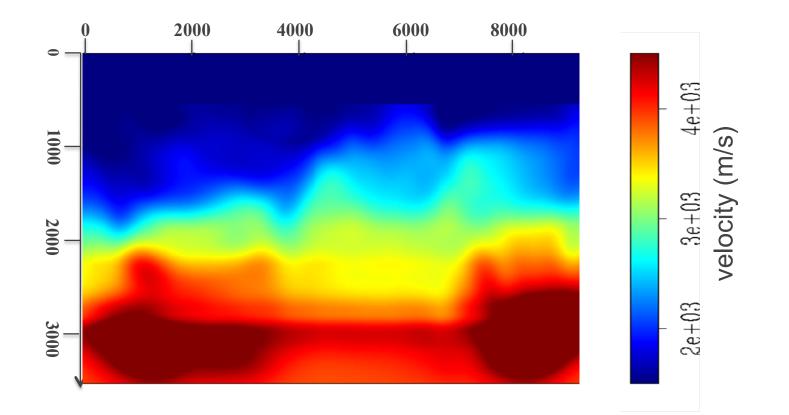
Marmousi model: true velocity



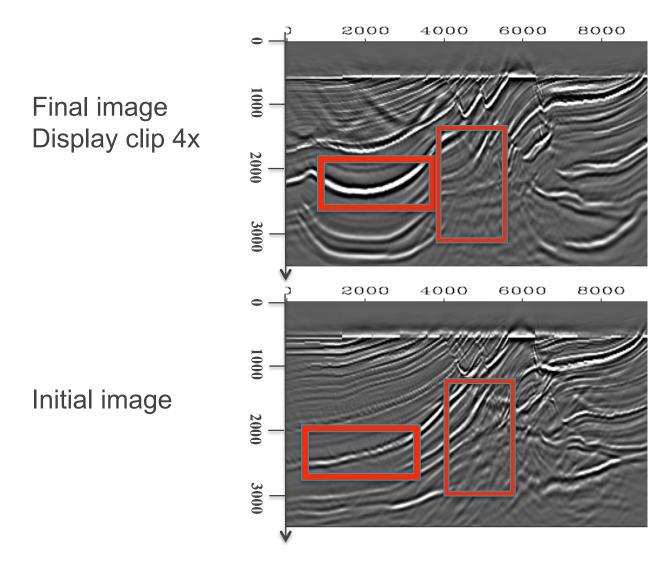
Starting velocity



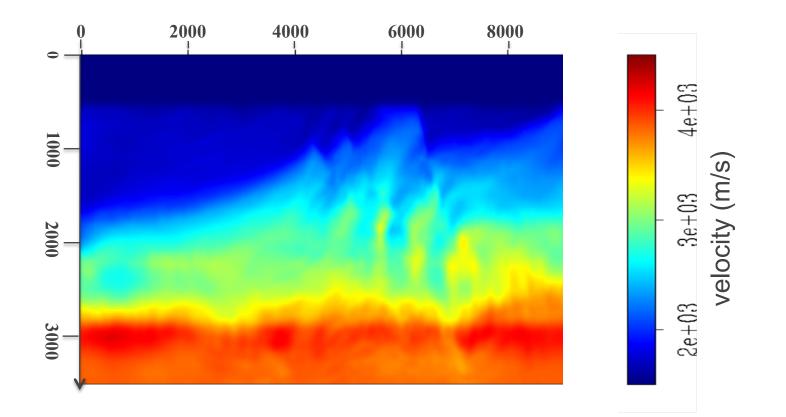
Partial-SPM without normalization (20 iterations)



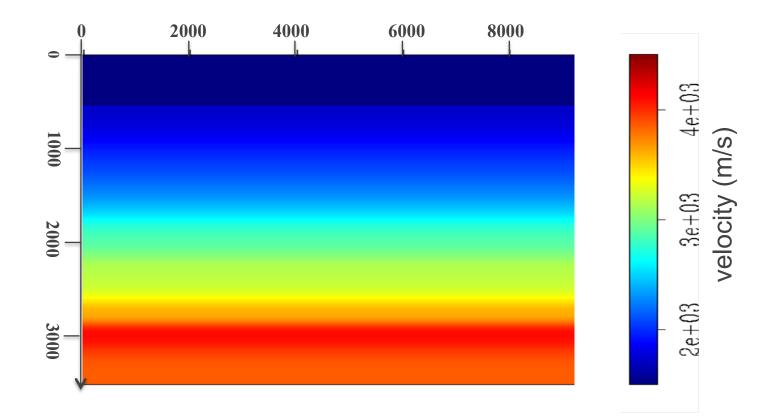
Partial-SPM without normalization



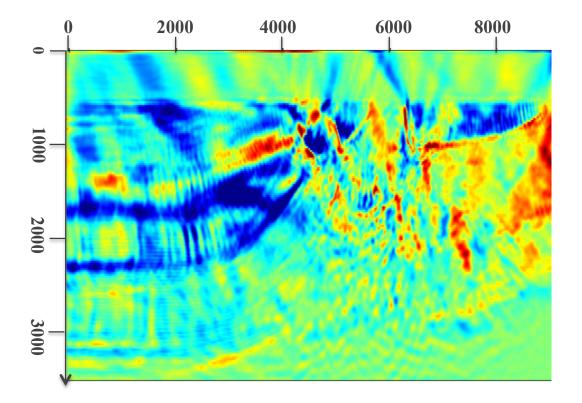
Normalized Partial stack power (40 iterations)



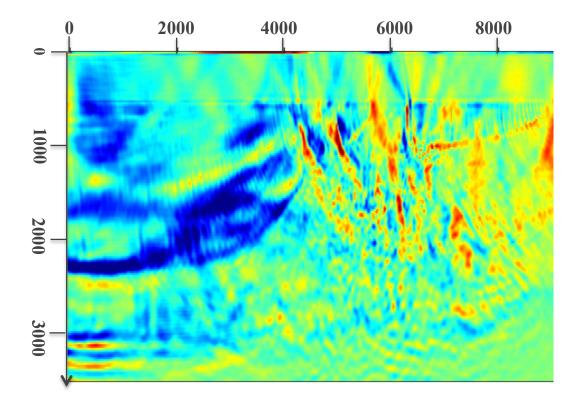
Marmousi test, normalized partial SPM method, starting model



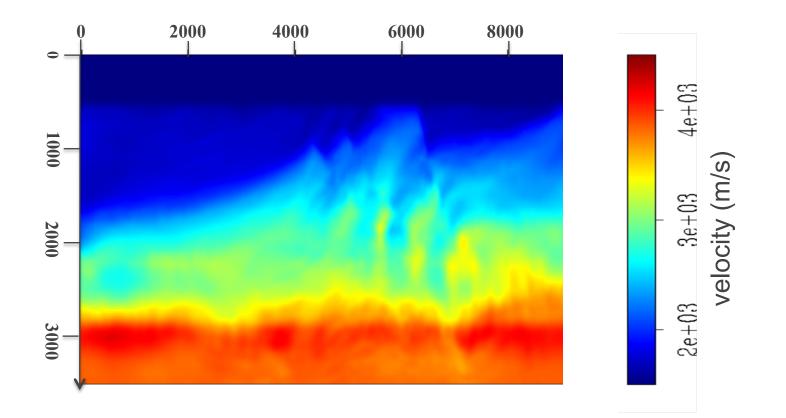
First update, Normalized partial stack power



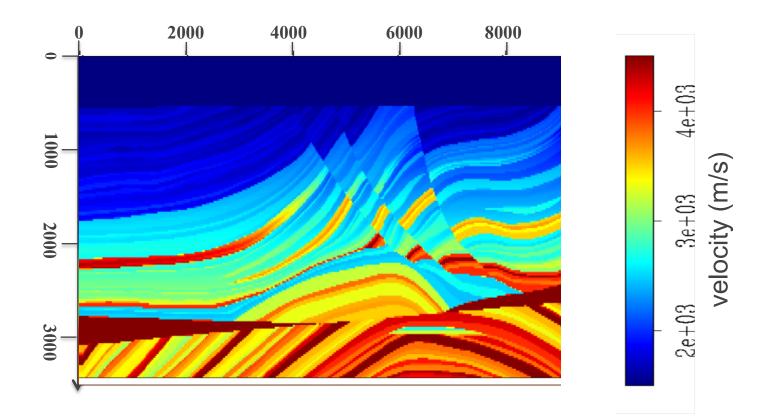
First update, Normalized DSO



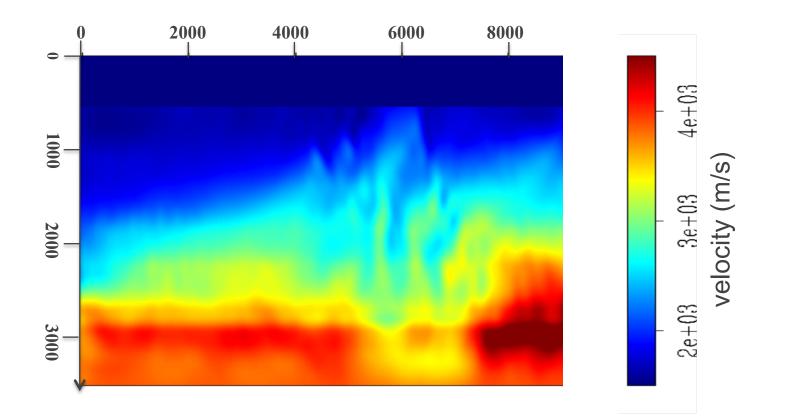
Normalized Partial stack power (40 iterations)



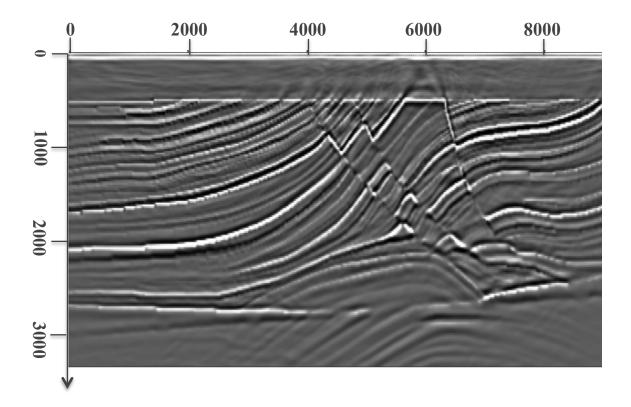
Normalized Partial stack power (40 iterations)



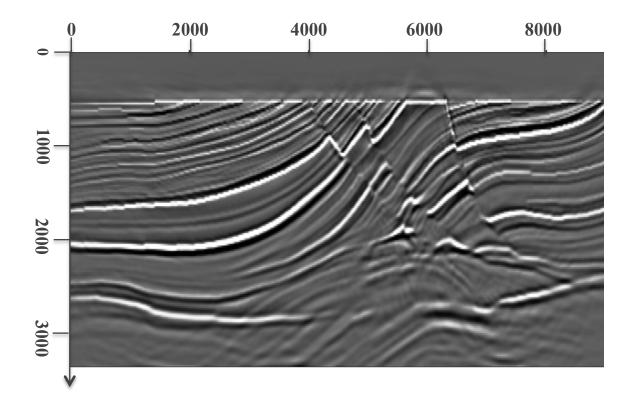
Normalized DSO (40 iterations)



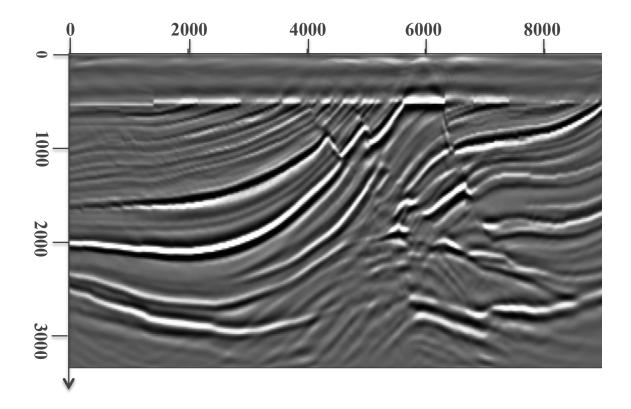
True image



Normalized Partial SPM



Normalized DSO



Conclusion & Discussion

- Partial SPM merges the merits of both SPM and DSO objective functions, also more flexible
- Normalization for reflector amplitude is not only preferred but necessary
- Remaining question:
 - Compared to data-domain, image-domain is easier to look at, but we are still missing the **ultimate correct** objective function

Conclusion & Discussion

- Partial SPM merges the merits of both SPM and DSO objective functions, also more flexible
 - Normalization for reflector amplitude is not only preferred but necessary
- Steering filters helps improves convergence speed and reduces the null space of the inverse problem
 - Most effective if the model is poorly constrained along the dipping direction
- Question Remained:
 - Compared to data-domain, image-domain is easier to look at, but we are still missing the **ultimate correct** objective function.
 - Is the steering filter always desirable? What if the geometry of the velocity model does not follow the reflectors', like BP 2004 model?

Acknowledgement

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