

On the Role of Deconvolution Imaging Condition in Full Waveform Inversion

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- □ CREWES is moving towards pratical application of FWI in recent years (Margrave et al. 2013).
- **Full Waveform Inversion (FWI) and Standard Inversion Methodology** (SM) (Margrave et al. 2012).
- □ Inverse Hessian and Illumination Compensation.
- □ Gradient with Illumination Compensation, Deconvolution Imaging Condition and Reflectivity.
- **Impedance Perturbation Estimation**
- **Well Control**
- □ Iterative Modeling and Migration and Inversion Method (Margrave et al. 2012).







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Deconvolution Imaging Condition

$$I(\mathbf{r}) = \int_{\omega}^{\omega_N} d\omega \frac{U(\mathbf{r},\omega)}{D(\mathbf{r},\omega)}$$

The reflectivity is given as the ratio of the upgoing wavefields and downgoing wavefields.

$$I(\mathbf{r}) = \int_{\omega}^{\omega_N} d\omega \frac{D^*(\mathbf{r}, \omega) U(\mathbf{r}, \omega)}{D^*(\mathbf{r}, \omega) D(\mathbf{r}, \omega) + \lambda A_{max}}$$

The complex conjugate of the downgoing wavefields D^* is always multiplied by in the denominator and numerator to make the imaging condition stable.







Cross-correlation Imaging Condition

$$I(\mathbf{r}) \simeq \frac{1}{A_D^2} \int_{\omega}^{\omega_N} d\omega D^*(\mathbf{r}, \omega) U(\mathbf{r}, \omega)$$
$$\simeq \int_{\omega}^{\omega_N} d\omega D^*(\mathbf{r}, \omega) U(\mathbf{r}, \omega)$$

The auto-correlation of the downgoing wavefields can be taken out from the integration.

$$I_{cross}(\mathbf{r}) = \sum_{\mathbf{r}_s} \int d\omega \Re\{\omega^2 \mathcal{F}_s(\omega) G(\mathbf{r}, \mathbf{r}_s, \omega) G(\mathbf{r}_g, \mathbf{r}, \omega) \psi^*(\omega)\}$$

Crosscorrelation imaging condition

$$I_{dec}(\mathbf{r}) = \frac{\sum_{\mathbf{r}_s} \int d\omega \Re\{\omega^2 \mathcal{F}_s(\omega) G(\mathbf{r}, \mathbf{r}_s, \omega) G(\mathbf{r}_g, \mathbf{r}, \omega) \psi^*(\omega)\}}{\sum_{\mathbf{r}_s} \int d\omega \Re\{\omega^4 | \mathcal{F}_s(\omega)|^2 | G(\mathbf{r}, \mathbf{r}_s, \omega)|^2 \psi^*(\omega)\} + \lambda A_{max}}$$

Deconvolution imaging condition







Analytic Solution of the Imaging Conditions









Numerical Example









Numerical Example









Numerical Example









$$\phi = \frac{1}{2} \|\mathbf{d} - \mathbf{B}\mathbf{u}\|_2$$

Misfit function in matrix form

$$g = \frac{\partial \phi}{\partial m} = \mathbf{J}^T \Delta d^*$$

Gradient

$$H_a = \mathbf{J}^T \mathbf{J}$$

Approximate Hessian







$$\delta m = -(\mathbf{J}^T \mathbf{J} + \lambda I)^{-1} (\mathbf{J}^T \Delta d^*) \simeq \delta m = -\frac{\mathbf{J}^T \Delta d^*}{\mathbf{J}^T \mathbf{J} + \lambda I}$$

Model Perturbation

$$\mathbf{B}(\mathbf{r},\omega)\mathbf{u}(\mathbf{r},\omega) = f(\mathbf{r},\omega)$$

Wave Equation







$$\delta m = -(\mathbf{J}^T \mathbf{J} + \lambda I)^{-1} (\mathbf{J}^T \Delta d^*) \simeq \delta m = -\frac{\mathbf{J}^T \Delta d^*}{\mathbf{J}^T \mathbf{J} + \lambda I}$$

Model Perturbation

$$\mathbf{B}\frac{\partial \mathbf{u}}{\partial m} = -\frac{\partial \mathbf{B}}{\partial m}\mathbf{u} \right\} \text{ SECONDARY SOURCE}$$

Scattered Source







$$\delta m = -(\mathbf{J}^T \mathbf{J} + \lambda I)^{-1} (\mathbf{J}^T \Delta d^*) \simeq \delta m = -\frac{\mathbf{J}^T \Delta d^*}{\mathbf{J}^T \mathbf{J} + \lambda I}$$

Model Perturbation

$$\mathbf{J} = \frac{\partial \mathbf{u}}{\partial m} = -\mathbf{B}^{-1} \frac{\partial \mathbf{B}}{\partial m} \mathbf{u}$$
Jacobian Matrix







$$g = -\sum_{\omega, \mathbf{r}_s} \omega^2 \Re \left\{ \mathbf{u}^T \otimes \left(\mathbf{B}^{-1} \right)^T \Delta d^* \right\}$$

Gradient

$$H_a = \left(\mathbf{B}^{-1} \frac{\partial \mathbf{B}}{\partial m} \mathbf{u}\right)^* \left(\mathbf{B}^{-1} \frac{\partial \mathbf{B}}{\partial m} \mathbf{u}\right)$$

Approximate Hessian







$$g = -\sum_{\omega, \mathbf{r}_s} \omega^2 \Re \left\{ \mathbf{u}^T \otimes \left(\mathbf{B}^{-1} \right)^T \Delta d^* \right\}$$

Gradient

$$H_{a} = \omega^{4} \Re \left(\mathbf{u}^{*} \mathbf{u} \left(\mathbf{B}^{-1} \right)^{*} \left(\mathbf{B}^{-1} \right) \right)$$

Approximate Hessian







$$g = -\sum_{\omega, \mathbf{r}_s} \omega^2 \Re \left\{ \mathbf{u}^T \otimes \left(\mathbf{B}^{-1} \right)^T \Delta d^* \right\}$$

Gradient

$$H_{a} = \omega^{4} \Re \left(\mathbf{u}^{*} \mathbf{u} \left(\mathbf{B}^{-1} \right)^{*} \left(\mathbf{B}^{-1} \right) \right)$$

Approximate Hessian

$$H_{pseudo} = f_{virtual}^* f_{virtual} = \left(\frac{\partial \mathbf{B}}{\partial m} \mathbf{u}\right)^* \left(\frac{\partial \mathbf{B}}{\partial m} \mathbf{u}\right) = \omega^4 \Re \left(\mathbf{u}^* \mathbf{u}\right)$$

Pseudo Hessian









Model Perturbation By Gary et.al (2011)







DECONVOLUTION IMAGING CONDITION



Model Perturbation







$$g = -\sum_{\omega, \mathbf{r}_s} \omega^2 \Re \left\{ A \frac{e^{ik_0 \tilde{\mathbf{r}}_s}}{4\pi \tilde{\mathbf{r}}_s} \otimes AR \frac{e^{-ik_0 \tilde{\mathbf{r}}_s}}{4\pi \tilde{\mathbf{r}}_s} \right\} = -\sum_{\omega, \mathbf{r}_s} \omega^2 \Re \left\{ \frac{1}{\tilde{\mathbf{r}}_s^2} \frac{A^2}{16\pi^2} R \right\}$$
Analytic Expression of the Gradient
ENERGY DECAY

$$H_{pseudo} = \Re \left\{ \omega^4 \mathbf{u}^*(\mathbf{r}'_s, \omega) \mathbf{u}(\mathbf{r}''_s, \omega) \right\} = \Re \left\{ \omega^4 \left(A \frac{e^{-i\kappa_0 \mathbf{r}_s}}{4\pi \tilde{\mathbf{r}}'_s} \right) \left(A \frac{e^{i\kappa_0 \mathbf{r}_s}}{4\pi \tilde{\mathbf{r}}''_s} \right) \right\}$$

Analytic Expression of Pseudo Hessian







$$g = -\sum_{\omega, \mathbf{r}_s} \omega^2 \Re \left\{ A \frac{e^{ik_0 \tilde{\mathbf{r}}_s}}{4\pi \tilde{\mathbf{r}}_s} \otimes AR \frac{e^{-ik_0 \tilde{\mathbf{r}}_s}}{4\pi \tilde{\mathbf{r}}_s} \right\} = -\sum_{\omega, \mathbf{r}_s} \omega^2 \Re \left\{ \frac{1}{\tilde{\mathbf{r}}_s^2} \frac{A^2}{16\pi^2} R \right\}$$
Analytic Expression of the Gradient
ENERGY DECAY
(11) $\Omega \left(A + \hat{\mathbf{r}}_s \right) = \Omega \left(A + \hat{\mathbf{r}}_s \right) \left(A + \hat{\mathbf{r}}_s \right) = \Omega \left(A + \hat{\mathbf{r}}_s \right) \left(A + \hat{\mathbf{r}}_s \right) = \Omega \left(A + \hat{\mathbf{r}}_s \right) \left(A + \hat{\mathbf{r}}_s \right) = \Omega \left(A + \hat{\mathbf{r}}_s \right) \left(A + \hat{\mathbf{r}}_s \right) = \Omega \left(A + \hat{\mathbf{r}}_s \right) \left(A + \hat{\mathbf{r}}_s \right) = \Omega \left(A + \hat{\mathbf{r}}_s \right) \left(A + \hat{\mathbf{r}}_s \right) = \Omega \left(A + \hat{\mathbf{r}}_s \right) \left(A + \hat{\mathbf{r}}_s \right) = \Omega \left(A + \hat{\mathbf{r}}_s \right) \left(A + \hat{\mathbf{r}}_s \right) = \Omega \left(A + \hat{\mathbf{r}}_s \right) \left(A + \hat{\mathbf{r}}_s \right) = \Omega \left(A + \hat{\mathbf{r}}_s \right) \left(A + \hat{\mathbf{r}}_s \right) = \Omega \left(A + \hat{\mathbf{r}}_s \right) \left(A + \hat{\mathbf{r}}_s \right) \left(A + \hat{\mathbf{r}}_s \right) = \Omega \left(A + \hat{\mathbf{r}}_s \right) \right)$

$$\mathbf{Diag}\left(H_{pseudo}\right) = \Re\left\{\omega^{4}\mathbf{u}^{*}(\mathbf{r}_{s},\omega)\mathbf{u}(\mathbf{r}_{s},\omega)\right\} = \Re\left\{\omega^{4}\left(A\frac{e^{-i\kappa_{0}\mathbf{r}_{s}}}{4\pi\tilde{\mathbf{r}}_{s}}\right)\left(A\frac{e^{i\kappa_{0}\mathbf{r}_{s}}}{4\pi\tilde{\mathbf{r}}_{s}}\right)\right\}$$

Analytic Expression of Diagonal Pseudo Hessian







$$\delta m \simeq \Re \left\{ \frac{-\sum_{\omega, \mathbf{r}_s} \omega^2 \frac{1}{\tilde{\mathbf{r}}_s^2} \frac{A^2}{16\pi^2} R}{\omega^4 \frac{A^2}{16\pi^2 \tilde{\mathbf{r}}_s^2}} \right\} = -\Re \left\{ \sum_{\omega} \omega^2 R \right\}$$

Analytic Expression of Model Perturbation **REFLECTIVITY**







$$R_n = \frac{I_{n+1} - I_n}{I_{n+1} + I_n} = \frac{\Delta I}{I_{n+1} + I_n}$$

Recall the relationship between the reflectivity and impedance at normal incidence

$$\Delta I \simeq 2I_n R_n$$

Impedance Perturbation or Impedance Imaging Condition

$$I_{k+1} = I_k + \Delta I_k = I_k + 2I_k R_k$$

Impedance can be updated iteratively









The slant gradient with different ray parameters are responsible to update the subsurface layers with different steep angles









Phase Encoded Source Wavefields and Plane-wave Source Wavefields Reproduced from Shan et al. (2006)







$$\tilde{g}(p_i^g,\omega) = -\int d\omega \Re \left\{ \omega^2 f_s(\omega) G(\mathbf{r},\mathbf{r}_s,\omega) G(\mathbf{r}_g,\mathbf{r},\omega) e^{i\omega p_i^g(x_s-x_g)} \delta P^* \right\}$$

Phase Encoded Gradient

$$\tilde{H}_{pseudo}\left(\mathbf{p}^{H},\omega\right) = \sum_{\mathbf{r}_{s}} \sum_{i=1}^{N_{p}^{H}} \int d\omega \Re \left\{ \omega^{4} G(\mathbf{r}'',\mathbf{r}_{s}',\omega) G^{*}(\mathbf{r}',\mathbf{r}_{s},\omega) e^{i\omega(p_{i}^{H}+\varepsilon\Delta p)(x_{s}'-x_{s})} \right\}$$

Phase Encoded Pseudo-Hessian







$$\tilde{g}(p_i^g,\omega) = -\int d\omega \Re \left\{ \omega^2 f_s(\omega) G(\mathbf{r},\mathbf{r}_s,\omega) G(\mathbf{r}_g,\mathbf{r},\omega) e^{i\omega p_i^g(x_s-x_g)} \delta P^* \right\}$$

Phase Encoded Gradient

$$\mathbf{Diag}\left(\tilde{H}_{pseudo}\left(\mathbf{p}^{H},\omega\right)\right) = \sum_{\mathbf{r}_{s}}\sum_{i=1}^{N_{p}^{H}}\int d\omega\Re\left\{\omega^{4}G(\mathbf{r},\mathbf{r}_{s}',\omega)G^{*}(\mathbf{r},\mathbf{r}_{s},\omega)e^{i\omega(p_{i}^{H}+\varepsilon\Delta p)(x_{s}'-x_{s})}\right\}$$

Phase Encoded Source Illumination or Phase Encoded Diagonal Pseudo-Hessian







$$\tilde{R} = \Re \left\{ \frac{\tilde{g}\left(p_{i}^{g}, \omega\right)}{\mathbf{Diag}\left(\tilde{H}_{pseudo}\left(\mathbf{p}^{H}, \omega\right)\right) / N_{p}^{H} + \lambda A_{max}} \right\}$$

Reflectivity Approximation Estimation or Phase Encoded Deconvolution Imaging Condition

$$\Delta I_k = 2I_k \tilde{R}_k$$

Impedance Perturbation Estimation







$$\tilde{R} = \Re \left\{ \frac{\tilde{g}\left(p_{i}^{g}, \omega\right)}{\mathbf{Diag}\left(\tilde{H}_{pseudo}\left(\mathbf{p}^{H}, \omega\right)\right) / N_{p}^{H} + \lambda A_{max}} \right\}$$

Reflectivity Approximation Estimation or Phase Encoded Deconvolution Imaging Condition

$$I_{k+1} = I_k + \Delta I_k = I_k + \mu_k \left(2I_k \tilde{R}_k \right)$$

Iterative Impedance Update





Iterative Modeling Migration and Inversion (IMMI)

As proposed by Gary et.al (2012), the estimation of the reflectivity using deconvolution imaging condition enables us to combine FWI with SM, which forms the *Iterative Modeling Migration and Inversion* (IMMI) method.

Table 1. Pseudo Code of IMMI Method

BEGIN $\leftarrow I_0$, initial model; **WHILE** $\epsilon \leq \epsilon_{min}$ or $k \leq k_{max}$ $\begin{array}{l}
\textbf{Modeling} \\
\textbf{Modeling} \\
\textbf{Modeling} \\
\begin{array}{l}
1. Identify the ray parameter <math>p_{i,k}^g \text{ for constructing the phase encoded gradient} \\
2. Identify the frequency band <math>f^k = f_0 \rightarrow f_{max}, f_{interval}, \text{ every } n \text{ iterations} \\
3. Generate the data residual <math>\delta P$ and apply low-pass filtering $\delta \tilde{P} = \textbf{low}_\textbf{pass} \left(\delta P, f^k\right) \\
4. Create the phase encoded gradient <math>\tilde{g}_k \left(p_{i,k}^g, \omega\right) \\
5. \textbf{FOR } i = 1 \text{ to } N_p^H, \text{ every } 1 \text{ or } m \text{ iterations} \\
\end{array}$ $\begin{array}{l}
\textbf{Migration} \\
\textbf{Migra$ $\begin{array}{l} \textbf{Inversion} \\ \textbf{S} \quad \textbf{END FOR} \\ \textbf{S} \quad \textbf{END FOR} \\ \textbf{S} \quad \textbf{Calculate the step length } \mu_k \text{ using the line search method} \\ \textbf{S} \quad \textbf{Calculate the step length } \mu_k \text{ using the line search method} \\ \textbf{S} \quad \textbf{Calculate the impedance:} \\ & I_{k+1} = I_k + 2\mu_k I_k \Re \left\{ \left(\textbf{Diag} \left(\tilde{H}_{pseudo}^k \left(\textbf{p}^H, \omega \right) \right) / N_p^H + \lambda \tilde{A}_{max} \right)^{-1} \tilde{g}_k \left(p_{i,k}^g, \omega \right) \right\} \\ \textbf{10. Calculate the relative least-squares error:} \\ & \epsilon = \frac{\|I_{k+1} - I_{true}\|_2}{\|I_{true}\|_2} \\ \textbf{END WHUE} \\ \end{array}$ END FOR END WHILE

Numerical Experiment









Numerical Experiment





Gradient with Single Shot





Gradient Comparison



(a) True Reflectivity



Normalized Amplitude





Gradient Comparison



(b) Cross-correlation Based Gradient



Normalized Amplitude





Gradient Comparison







Normalized Amplitude





Well Control





Well Control





Well Control





Estimated Reflectivity





Deconvolution Based Gradient after Well Control









True Impedance Perturbation









Impedance Perturbation Estimation









Inverted Impedance after 1st Iteration





Well Data Comparison









Phase Encoded Pseudo-Hessian





Diagonal Phase Encoded Hessian





Phase Encoded Pseudo-Hessian





Diagonal Phase Encoded Hessian





Slant Gradient



Slant Gradient with Ray Parameter p=-0.2s/km







Slant Gradient





Slant Gradient with Ray Parameter p=0.2s/km





Slant Gradient





Slant Gradient with Ray Parameter p=-0.3s/km





Phase Encoded Gradient





Phase Encoded Gradient without Precondition





Phase Encoded Gradient





Phase Encoded Gradient with Precondition









































The Bold-Red line, Black line and Bold-Blue line indicate the True Velocity Model, Initial Velocity Model and Inverted Velocity Model respectively.







Conclusions

- □ The gradient with illumination compensation can compensate the geometrical spreading effects, recover the amplitudes of the deep reflectors and can estimate the reflectivity directly.
- **The phase encoding method can reduce the computational cost effectively.**
- □ The IMMI method, which combines FWI and traditional impedance inversion method, is efficient and stable to reconstruct the velocity model.

Further Research Plan

- □ Apply the strategies proposed in this research on the Hussar practical datasets.
- **Incorporate AVO information in practical FWI (Innanen 2013).**





CREWES

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Thank You !



