Robust refraction statics solution using feedback from reflection data

Bernie Law and Daniel Trad, CREWES-University of Calgary*

Summary

Near surface models from refraction inversion contain several types of errors, which are partially compensated later in the data flow by reflection residual statics. In this work, we modify the dataflow to automatically include feedback information from reflection statics from stack-power maximization. This technique can work with any model based refraction solutions including grid based tomography model and layer based delay time methods. In this report we modify cost function of the refraction inversion by adding model and data weights computed from the long wavelength components of surface consistent residual statics. By using an iterative inversion, these weights allow us to update the near surface velocity model and to reject first arrival picks that do not fit the updated model. In this non-linear optimization work flow the refraction model is derived from maximizing the coherence of the reflection energy and minimizing the misfit between model arrival times and the recorded first arrival times. This approach can alleviate inherent limitations in shallow refraction data by using coherent reflection data.

Introduction

Near surface is known to have localized variations in material and velocity. Accurate measurements of these variations are essential to the success of imaging of deeper reflection event. However, shallow seismic reflection data are typically low fold and contaminated by surface noise; therefore, they are not suitable for near surface velocity model building. Refracted first arrivals from seismic reflection surveys have been used to compute near surface velocity model for initial static correction for most land seismic data processing. Without these initial statics corrections, subsequent reflection velocity analysis and residual statics computation can be compromised (Figure 1). However, refraction statics corrections often contain errors caused by the quality of the refraction data, numerical errors of the refraction solution and the inability of the refraction algorithm to model the actual physical properties of the near surface. This can result in unsatisfactory statics corrections and reflection images. These problems are often revealed on CDP stack sections, and are typically addressed by revising refraction algorithm parameters and constraints and by surface consistent residual statics using deeper reflection data. Ronen and Claerbout (1985) demonstrated that surface-consistent residual statics can be estimated by stack-power maximization. Statics estimation is effectively a velocity analysis of the near surface (Ronen and Claerbout, 1985); however, surface-consistent residual statics derived from more coherent and better sampled reflection data are not used in refraction inversion algorithms. Surface-consistent residual statics corrects for the three refraction errors caused by the refraction data, numerical errors of the model and the complexity of the near surface. In this paper, a refraction inversion work flow utilizing stack-power maximization to estimate the refraction data error, εd, and model error, εm, for improved near surface velocity model and refraction statics corrections will be discussed

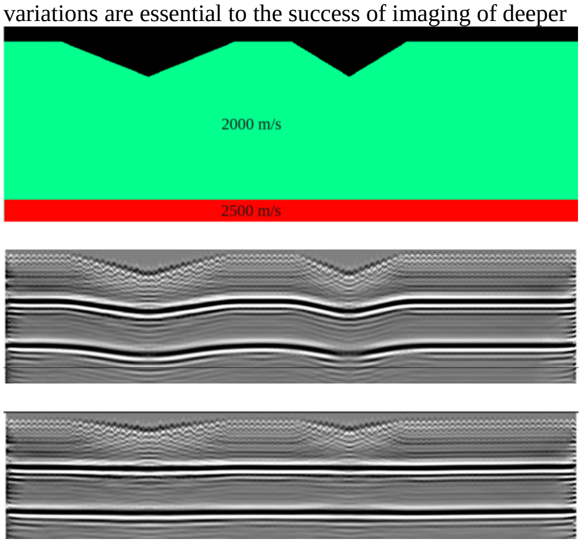

Figure 1: Velocity model with near surface velocity anomaly. CDP stack without statics correction. CDP stack after statics correction.

Theory and Method

Refraction solution can be cast as the inversion of near surface velocity model parameters **m** using first arrival time picks **d** and forward modeling operator **L**:

$$\mathbf{d} = \mathbf{Lm} \quad (1)$$

The model parameters **m** can be computed by minimizing the objective function **J**:

$$J = \| \mathbf{d} - \mathbf{Lm} \|^2 \quad (2)$$

Errors in the refraction solution arise when the modeling operator **L** is unable to model the data or the data are compromised because of near surface complexity. These errors often manifest as surface consistent residual statics in the subsequent processing steps as shown in figure 2a. In the proposed non-linear optimization work flow as shown

Robust refraction statics solution using feedback from reflection data

in figure 2b we add the model weight **Wm** and data weight **Wd** to the cost function of the inversion problem:

$$J = \| \mathbf{W_d}\, \mathbf{d} - \mathbf{W_d}\, \mathbf{L}\mathbf{W_m}\mathbf{m} \|^2 \qquad (3)$$

We use equation 4 and 5 to compute $\mathbf{W_m}$ and $\mathbf{W_d}$ for the GLI algorithm (Hampson and Russell 1984). **Wm** corrects for slowness and thickness errors and is computed from **E**, the long wavelength components of the surface consistent residual statics. $\mathbf{W_d}$ corrects for data errors and is computed from the misfit between **d** and $\mathbf{LW_m m}$.

$$\mathbf{W_m}\,(slowness) = 1 - 0.5{*}\mathrm{E}i \,/\, (\mathrm{Z}i\ \mathrm{P}i) \qquad (4)$$

$$\mathbf{W_m}\,(thickness) = 1 + 0.5{*}\mathrm{E}i \,/\, \mathrm{T}i \qquad (5)$$

$$\mathbf{W_{di}} = \begin{cases} 0, & \text{when } E_i \geq \varepsilon \text{ and } \delta t > K \\ 1, & \text{otherwise} \end{cases} \qquad (6)$$

where: $\mathrm{E}i = \mathrm{E}\ \mathrm{Z}i$ / Total thicknesss
$\mathrm{Z}i$ = thickness for layer i
$\mathrm{P}i$ = slowness for layer i
$\mathrm{T}i = \mathrm{Z}i / \mathrm{Vr} - \mathrm{Z}i\ \mathrm{P}i$
Vr = replacement velocity
ε = threshold for E_i
K = threshold for δt in terms of standard deviation of first arrival residual
δt = observed first arrival time – modeled first arrival time

Inversion procedure

1. Minimize $J=\| d - Lm \|^2$
2. Compute surface consistent residual static E using macro-binned stack-power maximization. Separate E into long wavelength and short wavelength components
3. Compute W_m and W_d
4. If required, repick first arrival times using $W_m m$ modeled first arrival times as constraints
5. Minimize $J = \| W_d\, d - W_d\, L\, W_m\, m \|^2$
6. Iterate 2 to 5 until convergence criteria are met

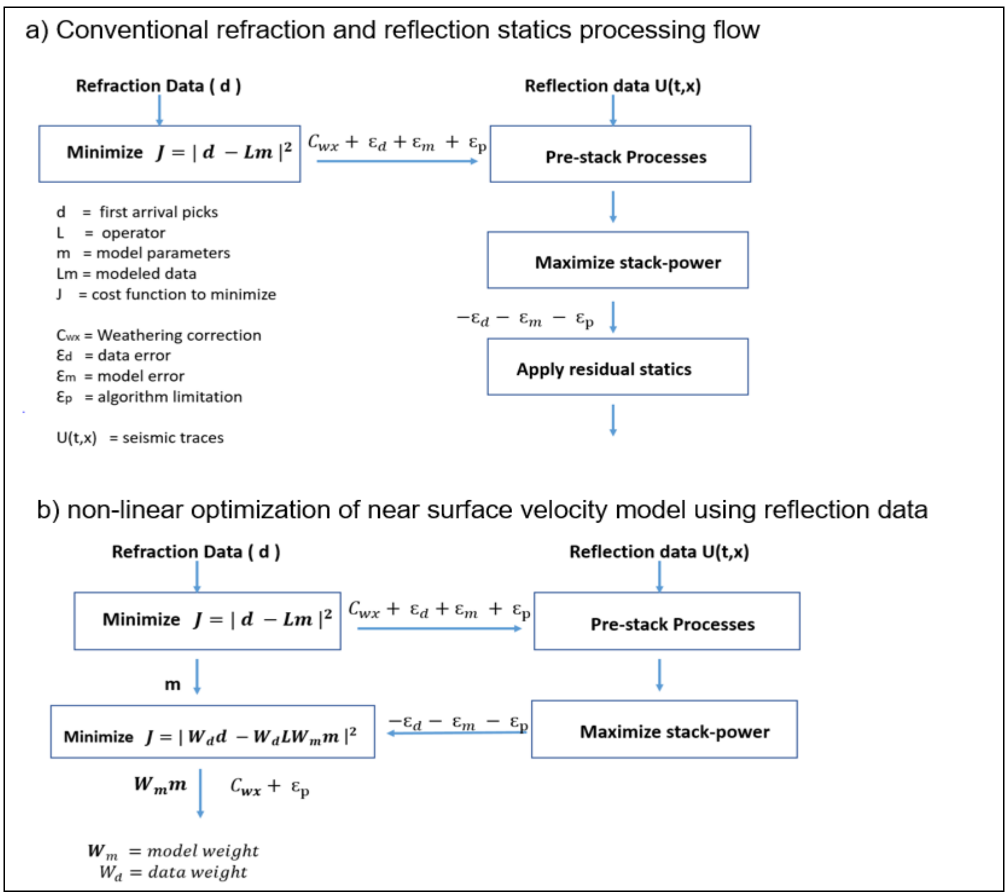

Figure 2: Conventional refraction statics processing flow versus non-linear optimization refraction statics processing flow.

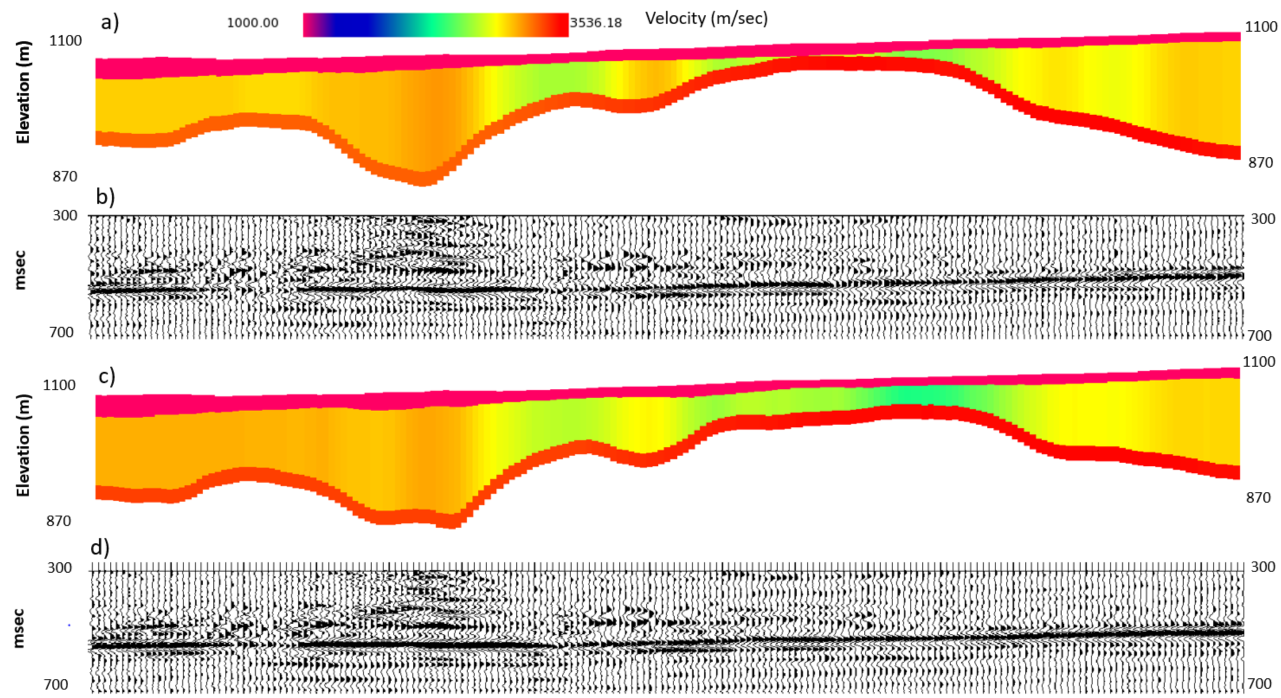

Figure 3: a) Initial GLI solution b) CDP stack after refraction correction from initial GLI solution c) GLI solution from non-linear optimization refraction statics processing flow. d) CDP stack after new refraction correction from new GLI solution.

This non-linear optimization method uses feedback from the correlations of reflection data to compute model weight $\mathbf{W_m}$. If the weighted near surface velocity model, $\mathbf{W_m\,m}$ is used to compute a new set of weathering statics corrections, the same reflection stack coherence can be achieved. However, this new model might not agree with refraction observations and can be incorrect, hence, not suitable for depth imaging or other inversion that requires an accurate and stable near surface velocity model. To harmonize the weighted near surface velocity model with the refraction observations, additional iterations of refraction inversion are required. We use W_m m as the starting model for the new iterations of the refraction inversion which can be layer based or grid based refraction tomography. However, without constraints to the actual first arrival picks, the refraction solution can potentially converge back to the previous solution and undo the effect of $\mathbf{W_m}$ that is not in agreement with the reflection coherence measurements. The new cost function described in equation 3, uses the data weight $\mathbf{W_d}$ to regularize the data space of the new inversion solution. The final near surface velocity model is now harmonized with the refraction observations at the near surface and with the reflection coherence of deeper reflection boundaries.

Examples

2D line 2008-SC-01 acquired near Spring Coulee, Alberta was used to test the proposed refraction statics processing flow. To impose a data limitation on the GLI algorithm we decimated the first arrival times picks by 75% using only every 4th shot points. Refraction statics correction computed from the initial GLI solution was applied to the seismic data prior to surface-consistent residual statics using the stack-power maximization algorithm. Long wavelength components of the surface-consistent residual statics were used to compute the **Wm** and **Wd** matrix for the next GLI iterations. Figure 3 compares GLI solution and CDP stack from conventional refraction statics processing flow to the proposed refraction statics processing flow using feedbacks from stack-power maximization. CDP stack from the new GLI solution shows significant uplifts in coherence. As shown in figure 3c, a geological plausible improvement to the near surface velocity model that agrees with reflection coherence of deep reflection events has been achieved. This new model should be better suited for depth imaging and other inversion processes.

Robust refraction statics solution using feedback from reflection data

Refraction Tomography

Refraction tomograpghy can be posted as a discrete linear inverse problem:

$$\underline{G}\ \underline{m} = \underline{d} \qquad (7)$$

$$\underline{G} = \begin{bmatrix} L1,1 & L1,2 & L1,3 & L1,4 & L1,5 & .. & L1,m \\ L2,1 & L2,2 & L2,3 & L2,4 & L2,5 & .. & L2,m \\ L3,1 & L3,2 & L3,3 & L3,4 & L3,5 & .. & L3,m \\ .. & .. & .. & .. & .. & .. & .. \\ Ln,1 & Ln,2 & Ln,3 & Ln,4 & Ln,5 & .. & Ln,m \end{bmatrix} \qquad (8)$$

$$\underline{m} = \begin{bmatrix} \Delta M1 \\ \Delta M2 \\ \Delta M3 \\ .. \\ \Delta Mm \end{bmatrix} \qquad \underline{d} = \begin{bmatrix} \Delta T1 \\ \Delta T2 \\ \Delta T3 \\ .. \\ \Delta Tn \end{bmatrix} \qquad (9)$$

where: Li,j = ray segment length for ray path i and cell j
ΔMj= model update for cell j
ΔT i= model update for cell ray path i

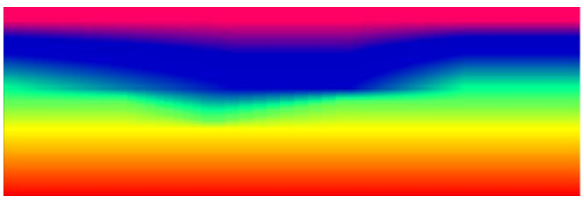
Figure 4a: Reference model

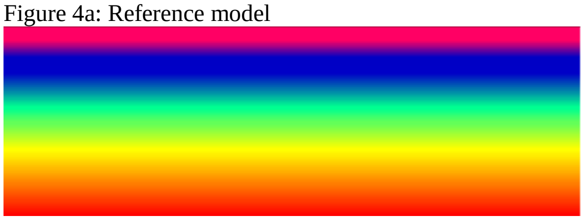
Figure 4b:Starting model

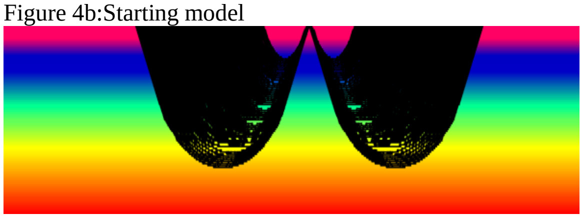
Figure 4c: ray paths

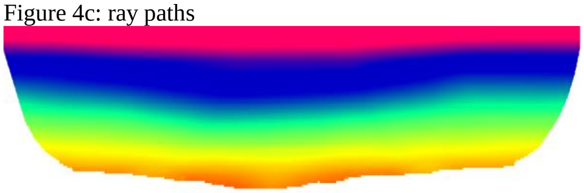

Figure 4d: tomographic inversion result after 4 iterations.

Similar to GLI inversion, model weight $\mathbf{W_m}$ and data weight $\mathbf{W_d}$ can be incorporated in the refraction tomography:

$$\underline{\mathbf{W_d}}\ \underline{\mathbf{W_m}}\ \underline{G}\ \ \underline{m} = \underline{\mathbf{W_d}}\ \underline{d} \qquad (10)$$

$$\mathbf{W_m} = 1 - E / \mathrm{Sum}(dz^* P_{iz}) \quad ;\ iz=1 \text{ to idatum} \qquad (11)$$

where: E = long wavelength components of the surface consistent residual statics.
dz = depth step of the velocity model.
idatum = the depth of intermediate datum for weathering statics correction.

$\mathbf{W_{di}}$ can be computed using equation (6)

Conclusions

Refraction first arrivals are used for near surface velocity model building because shallow seismic reflection events are typically characterized by low fold and contaminated by surface noises and not suitable for near surface velocity inversion. However, reflection coherence measurements from deeper and more coherent seismic reflection events can reveal errors in the near surface velocity model computed from refraction inversion. We modify the cost function of refraction inversion to incorporate model space and data space regularization that harmonize the refraction solution with the stack power of the deeper and more coherent seismic reflection. We use residual statics from reflection data to compute the model weight W_m and data weight W_d for the new cost function of this non-linear optimization process. Test results confirm the proposed iterative refraction statics processing flow can alleviate limitations in refraction data and refraction algorithms. Test results show improvement to the coherence of the reflection image and geological plausible improvement in the near surface velocity model. Near surface velocity model from this process is harmonized with the near surface refraction observations and with the reflection coherence of deeper reflection boundaries and is better suited for depth imaging and other inversion processes that require an accurate and stable near surface velocity model.

Acknowledgments

This work was funded by CREWES industrial sponsors and NSERC (Natural Science and Engineering Research Council of Canada) through the grant CRDPJ 46119-13.