A nonlinear differential-semblance algorithm for waveform inversion

Dong Sun

The Rice Inversion Project

Annual Review Meeting

March 30, 2012





Full Waveform Inversion

2 Extension and Differential Semblance Optimization (DSO)





Full Waveform Inversion (FWI)

A usual set-up:

- $\mathcal{M} = a$ set of models ({ $m(\mathbf{x})$ }), $\mathcal{D} = a$ space of data
- $\mathcal{F} : \mathcal{M} \to \mathcal{D}$ forward map

FWI (least-squares inversion): given $d_o \in \mathcal{D}$, solve

$$\min_{m \in \mathcal{M}} J_{LS} := \frac{1}{2} \left\| \mathcal{F}[m] - d_o \right\|^2 \quad [+ \text{ regularizing term(s)}]$$

Note:

- FWI globally minimize the objective using local methods
- observed data d_o = ∏_s d_o(x_r, t; s) highly redundant & band-limited
 possibilities for acquisition parameter s include source position, offset, slowness (plane wave data),...



Full Waveform Inversion (FWI)

Studied since the 80's, becoming feasible in last 10 yrs:

- + accommodates any modeling physics & provides quantitative inferences of subsurface (some spectacular successes)
- $\pm\,$ applicable to long-offset surface data (diving and refracted waves); most of successful inversions so far involve transmitted data

inversion with reflection data still a challenge

fundamental obstacles:

- 1. spectral data incompleteness missing low frequencies in data leads to missing long scale components in estimated model
- 2. strong nonlinearity, many false local minima descent methods fail



Full Waveform Inversion (FWI)

Remedies for reflection inversion:

- automatic migration velocity analysis (MVA) (e.g., DSO variants): decompose model into slowly & fast varying parts (background & reflectivity), then alternately
 - a. build reflectivity via migration or linearized LS-inversion
 - b. update background to reduce inconsistency of reflectivity gathers
 - + infer global changes in model (long-scale updates)
 - limited by linearization and scale separation assumptions
- ✓ nonlinear DSO: import MVA's concepts (image gathering, semblance measuring) into FWI and drop MVA limitations





Full Waveform Inversion

2 Extension and Differential Semblance Optimization (DSO)





Formulate FWI via DSO

Concept: relax FWI via extension then demand coherence of extended model FWI - attempt to match all data simultaneously with one model $\min_{m \in \mathcal{M}} \frac{1}{2} \|\mathcal{F}[m] - d\|^2 := \frac{1}{2} \sum_s \left(\|\mathcal{F}[m](s) - d(s)\|^2 \right)$

Extended WI - fit subsets of data with non-physical extended models

$$\min_{\bar{m}\in\overline{\mathcal{M}}} \frac{1}{2} \left\| \overline{\mathcal{F}}[\bar{m}] - d \right\|^2 := \frac{1}{2} \sum_{s} \left(\left\| \mathcal{F}[\bar{m}(.,s)](s) - d(s) \right\|^2 \right)$$

Note:

• extended models
$$\overline{\mathcal{M}} = \{\overline{m}(\mathbf{x}, s)\}$$
 $(\mathcal{M} \subset \overline{\mathcal{M}}, \text{ regarding } \overline{m} = m \text{ iff } \overline{m}(\mathbf{x}, s) = m(\mathbf{x}) \text{ for all } s)$

• extended modeling $\overline{\mathcal{F}}: \overline{\mathcal{M}} \to \mathcal{D}$ by $\overline{\mathcal{F}}[\overline{m}](s) = \mathcal{F}[\overline{m}(\cdot, s)](s)$

Equivalent problem to FWI - find coherent solution to extended WI

Formulate FWI via DSO

Differential Semblance (with surface oriented extension):

- s finely sampled \Rightarrow coherence criterion is $\partial \bar{m}/\partial s = 0$
- Differential Semblance Optimization:

$$\min_{\bar{m}\in\overline{\mathcal{M}}} \quad J_{DS}[\bar{m}] := \frac{1}{2} \left\| \frac{\partial}{\partial s} \bar{m} \right\|^2$$

s.t. $\left\| \overline{\mathcal{F}}[\bar{m}] - d \right\| \approx 0$

(coherence measurement)

(data-fitting constraints)

Key to success: need a proper control in order to navigate through the feasible model set

$$\left\{ \bar{m} \in \overline{\mathcal{M}} : \left\| \overline{\mathcal{F}}[\bar{m}] - d \right\| \approx 0 \right\}$$



Using LF data as control

Concept:

Cannot use independent long-scale model as control, as in MVA: "low spatial frequency" not well defined, depends on velocity.

However, temporal passband is well-defined, and observed data lacks very low frequency energy (0-3, 0-5,... Hz) with good s/n

Generally, the impulsive inverse problem is solvable: LS inversion leads to "unique" model, if data d is *not* band-limited (good s/n down to 0 Hz)

 $\mathsf{So:}$ use low-frequency data as control (analogous to long-scale model in $\mathsf{MVA})$



Using LF data as control

Approach I: use low-frequency data as control

- define low-frequency source complementary to missing passband, low-frequency modeling op \mathcal{F}_l and its extension $\overline{\mathcal{F}_l}$
- define complementary low-frequency data d_l
- define $ar{m}[d_l]$ to be minimizer of

$$\left\|\overline{\mathcal{F}}[\bar{m}] + \overline{\mathcal{F}}_{l}[\bar{m}] - (d+d_{l})\right\|^{2} + \sigma^{2} \left\|\frac{\partial \bar{m}}{\partial s}\right\|^{2}$$

- nDSO: determine d_l by solving

$$\min_{d_l} \left\| \frac{\partial}{\partial s} \bar{m}[d_l] \right\|^2$$

Initial exploration: D. Sun (2008), D. Sun & W. Symes (2009), for plane wave / layered medium modeling – slices of DS objective are convex, i.e., an enlargement of the domain of attraction of the global minimum is achieved

Further thought: find a way to supply meaningful/consistent low frequency data



Using LF data as control

Approach II: generate low-frequency data from model

- Given *low frequency control model* $m_l \in M$, define extended model $\bar{m} = \bar{m}[m_l]$ by minimizing

$$\|\overline{\mathcal{F}}[\bar{m}] + \overline{\mathcal{F}}_{l}[\bar{m}] - (d + \mathcal{F}_{l}[m_{l}])]\|^{2} + \sigma^{2} \left\|\frac{\partial \bar{m}}{\partial s}\right\|^{2}$$

- nDSO: determine m_l by solving

$$\min_{m_l} \left\| rac{\partial}{\partial s} ar{m}[m_l]
ight\|^2$$

Advantage of this approach: m_l plays same role as migration velocity model, but no linearization, scale separation assumptions required by formulation.

Current project: 2D constant-density acoustics, plane-wave sources (to minimize edge artifacts)

DSO Algorithm

Key step: compute m_l gradient:

$$\nabla J_{DS}[m_l] = -D\mathcal{F}_l[m_l]^T D\overline{\mathcal{F}}_l[\bar{m}[m_l]] H[\bar{m}[m_l]]^{-1} \frac{\partial^2}{\partial s^2} \bar{m}[m_l]$$

where

$$H[\bar{m}] = \left(D\overline{F}[\bar{m}] + D\overline{F_l}[\bar{m}]\right)^T \left(D\overline{F}[\bar{m}] + D\overline{F_l}[\bar{m}]\right)$$

Computational procedure:

- initialize m_l, etc.
- 2 solve sub-LS problem for $\bar{m}[m_l]$
- **③** evaluate $J_{DS}[\bar{m}]$. If stopping criterion satisfied, stop; else, continue.
- compute updating direction $g = -\nabla J_{DS}[m_l]$
- update m_l , cycle







3 Examples: Inversion in Layered Medium



Model



Three layer bulk modulus model. (acoustic velocity $v = 1.5, 2.5, 2 \,\mathrm{km/s}$, density $\rho = 1 \,\mathrm{g/cm^3}$)

Two sets of inversion exercises:

- absorbing surface
- free surface



Absorbing Surf: LS Inversion (standard FWI)



Band limited (5-12-36-45 Hz) plane wave source - 31 slowness panels



Absorbing Surf: LS Inversion (standard FWI)







Absorbing Surf: LS Inversion (standard FWI)



Left: FWI estimate of bulk modulus after 40 LBFGS iterations; Right: final model slice at $x=1.5(\,\rm km)$



Inverted model $\bar{m}[m_l]$, m_l = homogeneous model





Inverted gather $\bar{m}[m_l]\text{,}~m_l = \text{homogeneous model}\text{,}~x = 1.5~\text{km}$



Low frequency control model m_l after 7 updates





Inverted gather $\bar{m}[m_l]$, 7 updates of m_l , $x=1.5~{\rm km}$





Left: m_l at x = 1.5 (km); Right: final model at x = 1.5 (km)

















Data residual after 60 LBFGS iterations - RMS $\sim 8\%$





Inverted model gather $\bar{m}[m_l]$, m_l = homogeneous model, x = 1.5 km





Low frequency control model m_l in the 3rd DS-iteration





Inverted model $\bar{m}[m_l]$ in the 3rd DS-iteration





Inverted model gather $\bar{m}[m_l]$ after 3 DS-iterations, $x=1.5~{\rm km}$ DS-objective value reduced by 60%





Target Data (Top), Data Residual (Bottom) :after 60 LBFGS iterations - RMS \sim 15% (in 3rd DS iteration)





Left: m_l at x = 1.5 (km); Right: final model at x = 1.5 (km)





Inverted model stack (in 3rd DS iteration)



Standard LS inversion staring from the final model stack from nDSO



Inverted model after 153 LBFGS iterations (RMS residual \sim 6%) (initial RMS res \sim 77%; after 30 LBFGS RMS res \sim 14%)



Standard LS inversion staring from the homogeneous model



Inverted model after 30 LBFGS iterations (RMS residual \sim 27%)





Data fitting (for shot with slowness 0): Left, target data; Middle, residual for LS inv from DS-fnl-stack; Right, residual for LS inv from homogeneous model



Left: LS inv fnl model at x = 1.5 (km); Right: nDS inv fnl model at x = 1.5 (km)

Remarks

Pros:

- successfully infers global model updates for both absorbing surface and free surface $% \left({{{\mathbf{r}}_{{\mathbf{r}}}}_{{\mathbf{r}}}} \right)$

- stack at least gives a good initial model for LS-FWI



Remarks

Cost: 3-7 DS-iterations, mainly consisting of:

• 1 LS inversion (for $\bar{m}[m_l]$)

• direction computation $g = D\mathcal{F}_l[m_l]^T D\overline{\mathcal{F}}_l[\bar{m}[m_l]]H[\bar{m}[m_l]]^{-1} \frac{\partial^2}{\partial s^2} \bar{m}[m_l]$

• solve $H[\bar{m}[m_l]]q = \frac{\partial^2}{\partial s^2}\bar{m}[m_l]$ for $q \ (\sim 30 \ \text{CG} \ \text{iterations})$

to reduce cost: (a) pre-conditioning; (b) scaling strategies; (c) replacing ${\cal H}$ with I (might work) \ldots

• compute $g = D\mathcal{F}_l[m_l]^T D\overline{\mathcal{F}}_l[\bar{m}[m_l]] q$ (1 Born Sim + 1 Adj Comp)

• step-length computation (1 CG or Lin-LS + 1 Born Sim):

$$\alpha = -\frac{\langle \psi, \frac{\partial}{\partial s}\bar{m}[m_l] \rangle}{\langle \psi, \psi \rangle}$$

, where $\psi=\frac{\partial}{\partial s}\left(D\overline{F}[\bar{m}[m_l]]^{\dagger}\;DF[m_l]g\right)$



Summary

This approach may:

- combine best features of MVA and FWI (no linearization, scale separation assumptions required),
- address the spectral data incompleteness and local-minima issue,
- infer global changes in model and provide good initial model for FWI.

Next to-do: explore this strategy with more tests, improve efficiency, ...



Acknowledgements

Great thanks to

- my Ph.D. committee: William Symes, Matthias Heinkenschloss, Yin Zhang, Colin Zelt
- Present and former TRIP team members: Xin Wang, Marco Enriquez, Igor Terentyev, Tanya Vdovina, Rami Nammour
- ExxonMobil URC FWI team especially Dave Hinkley, Jerry Krebs
- WesternGeco FWI Management for support and permission to present here
- Sponsors of The Rice Inversion Project
- NSF DMS 0620821

Thank you!

