Source function estimation in extended full waveform inversion

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Objective

Recover Earth model with seismic waveform inversion

Problems

Unknown source

Local minima

Solution

Variable projection method

Extended modelling concept

Abstract setting for forward map $\mathcal{F}:\mathcal{M}\rightarrow\mathcal{D}$

$$F[m] = d$$

F: forward modelling operator m: model (v, r, w)d: sampled pressure data at receivers

Extended forward map $\bar{\mathcal{F}}: \bar{\mathcal{M}} \to \mathcal{D}$ [Symes, 2008]

$$\bar{F}[\bar{m}] = d$$

- \bar{F} : extended forward modelling operator
- $ar{m}$: extended model ($v(\mathbf{x})$, $ar{r}(\mathbf{x},\mathbf{h})$, w(t), ...)
- d: sampled pressure data at receivers

Linearized acoustic modelling (Born approximation)

p - reference (incident) pressure field

$$\left(\frac{1}{v^2(\mathbf{x})}\frac{\partial^2}{\partial t^2} - \nabla^2\right)p(t, \mathbf{x}; \mathbf{x_s}) = w(t)\delta(\mathbf{x} - \mathbf{x_s})$$

 δp - scattered (perturbation) pressure field

$$\left(\frac{1}{v^2(\mathbf{x})}\frac{\partial^2}{\partial t^2} - \nabla^2\right)\delta p(t, \mathbf{x}; \mathbf{x_s}) = \frac{2\bar{r}(\mathbf{x}, \mathbf{h})}{v^2(\mathbf{x})}\frac{\partial^2 p}{\partial t^2}(t, \mathbf{x}; \mathbf{x_s})$$

 $\begin{array}{l} w(t): \text{ source function} \\ v: \text{ velocity of seismic waves} \\ \bar{r}(\mathbf{x},\mathbf{h}) = \frac{\delta \bar{v}(\mathbf{x},\mathbf{h})}{v(\mathbf{x})}: \text{ extended reflectivity } (\bar{v}(\mathbf{x},\mathbf{h}): \text{ extended velocity}) \\ p: \text{ pressure field} \\ \mathbf{x}: \text{ position in earth model} \\ \mathbf{x}_s: \text{ source location} \end{array}$

Green's function

 $G(t,\mathbf{x};\mathbf{x}_s)$ - Green's function, impulse response of the medium

$$\left(\frac{1}{v^2(\mathbf{x})}\frac{\partial^2}{\partial t^2} - \nabla^2\right)G(t, \mathbf{x}; \mathbf{x_s}) = \delta(t)\delta(\mathbf{x} - \mathbf{x_s})$$

$$p(t, \mathbf{x}; \mathbf{x}_s) = G(t, \mathbf{x}; \mathbf{x}_s) * w(t)$$
$$\delta p(t, \mathbf{x}_r; \mathbf{x}_s) = \bar{f}[v]\bar{r} * w(t)$$

$$\begin{split} \delta p(t, \mathbf{x}_r; \mathbf{x}_s) &= \left[\frac{\partial^2}{\partial t^2} \int d\mathbf{x} \int d\mathbf{h} \frac{2\bar{r}(\mathbf{x}, \mathbf{h})}{v^2(\mathbf{x})} G(t, \mathbf{x} + \mathbf{h}; \mathbf{x}_r) * G(t, \mathbf{x} - \mathbf{h}; \mathbf{x}_s) \right] * w(t) \\ &= \bar{f}[v]\bar{r} * w(t) \end{split}$$

Extended full waveform inversion (EFWI)

Abstract setting for Inversion:

$$m = F^{-1}[d]$$

- This inverse problem is large scale and nonlinear.
- Indirect approach: formulate as an optimization problem

Given d, find m that minimizes the output least square (OLS) objective function (Tarantola, Lailly, 1980s to present)

$$min_m J_{OLS}[m,d] = \frac{1}{2} \|F[m] - d\|^2$$

$$min_{v,\bar{r},w}J[v,\bar{r},w,d] = \frac{1}{2} \|\bar{f}[v]\bar{r} * w - d\|^2 + \frac{\alpha^2}{2} \|A\bar{r}\|^2$$

Source function w(t) in EFWI

$$J = \frac{1}{2} \|\bar{f}[v]\bar{r} * w - d\|^2 + \frac{\alpha^2}{2} \|A\bar{r}\|^2$$

Following [Rickett, 2013]'s approach, write in two matrix forms

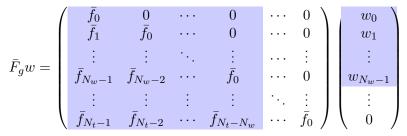
$$J = \frac{1}{2} \|\bar{F}_g[v,\bar{r}]w - d\|^2 + \frac{\alpha^2}{2} \|A\bar{r}\|^2$$
(1)

$$J = \frac{1}{2} \|W\bar{f}[v]\bar{r} - d\|^2 + \frac{\alpha^2}{2} \|A\bar{r}\|^2$$
(2)

 $\bar{F}_g[v, \bar{r}]$: matrix that applies convolutions to wW: matrix that applies convolution to $\bar{f}[v]\bar{r}$

1st form

$$J = \frac{1}{2} \|\bar{F}_g[v,\bar{r}]w - d\|^2 + \frac{\alpha^2}{2} \|A\bar{r}\|^2$$



 N_w : number of time samples for source wavelet signature N_t : number of time samples for recorded seismic data

Variable Projection Method (VPM) [Golub and Pereyra, 1973]

$$min_{v,\bar{r},w}J_{OLS}[v,\bar{r},w,d] = \frac{1}{2}\|\bar{F}_g[v,\bar{r}]w - d\|^2 + \frac{\alpha^2}{2}\|A\bar{r}\|^2$$

VPM

- Step 1: eliminate the linear variable (w)
- Step 2: minimize the reduced objective function (v, \bar{r})
- Step 3: use the optimal value (v, \bar{r}) to solve for w

The constrained equation [Rickett, 2013]

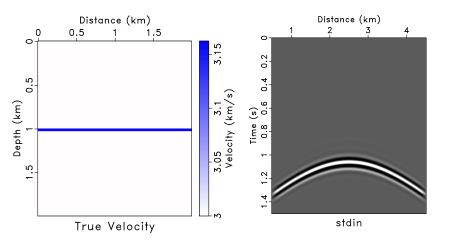
$$w = \bar{F}_{g}^{+}d = \left(\bar{F}_{g}^{*}\bar{F}_{g}\right)^{-1}\bar{F}_{g}^{*}d$$

Reduced objective function

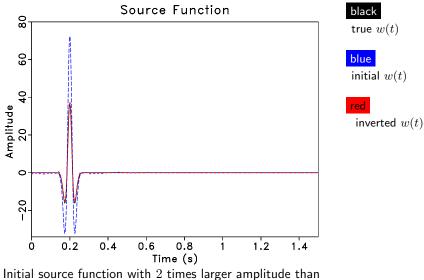
$$min_{v,\bar{r}}J_{OLS}[v,\bar{r},d] = \frac{1}{2} \|\bar{F}_g\bar{F}_g^+d - d\|^2 + \frac{\alpha^2}{2} \|A\bar{r}\|^2$$

 $\bar{F}_g^+[v,\bar{r}]$: the pseudo-inverse of $\bar{F}_g[v,\bar{r}]$. $\bar{F}_g^*\bar{F}_g$: dimensions of $N_w\times N_w$, inverted easily with direct methods.

Test

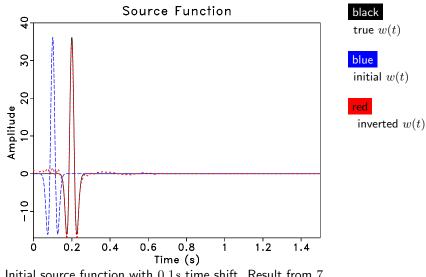


Inverted source function w(t) (wrong amplitude)



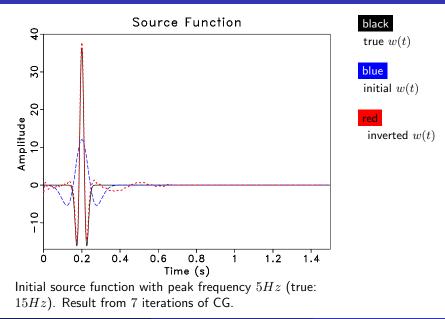
Initial source function with 2 times larger amplitude that the true one. Result from 7 iterations of CG.

Inverted source function w(t) (time shift)



Initial source function with 0.1s time shift. Result from 7 iterations of CG.

Inverted source function w(t) (peak frequency)



Reduced objective function

$$min_{v,\bar{r}}J_{OLS}[v,\bar{r},d] = \frac{1}{2}\|\bar{F}_g\bar{F}_g^+d - d\|^2 + \frac{\alpha^2}{2}\|A\bar{r}\|^2$$

Advantages [Golub and Pereyra, 2003]:

- The reduced problem has the same minima as the original one
- Eliminate the linear variable

Reduced objective function

$$min_{v,\bar{r}}J_{OLS}[v,\bar{r},d] = \frac{1}{2} \|\bar{F}_g[v,\bar{r}]\bar{F}_g^+[v,\bar{r}]d - d\|^2 + \frac{\alpha^2}{2} \|A\bar{r}\|^2$$

Nested approach [Symes and Kern, 1994, Almomin and Biondi, 2013]

- 1. Inner optimize over \bar{r} for each \boldsymbol{v}
- 2. Outer optimize over v
- 1. Gradient of J with respect to \bar{r} (nonlinear)

 $\nabla_{\bar{r}}J = \bar{f}[v]^* W[v,\bar{r}]^* d_r + \alpha^2 A^* A \bar{r}$

data residual: $d_r = \bar{F}_g[v, \bar{r}]\bar{F}_g^+[v, \bar{r}]d - d$

1. Gradient of J with respect to \bar{r}

$$\nabla_{\bar{r}}J = \bar{f}[v]^* W[v,\bar{r}]^* d_r + \alpha^2 A^* A \bar{r}$$

data residual:
$$d_r = \bar{F}_g[v, \bar{r}]\bar{F}_g^+[v, \bar{r}]d - d$$

2. Gradient of J with respect to v

$$\nabla_v J = D\bar{f}^* \left(W[v,\bar{r}]^* d_r, \bar{r}[v] \right)$$

- Finite difference C code in Madagascar
- TAPENADE Online Automatic Differentiation Engine derivative \$\bar{f}[v]\$ and its adjoint \$\bar{f}[v]^*\$ (dot product test) 2nd order derivative \$\bar{D}f[v]\$ and its adjoint \$\bar{D}f[v]^*\$ (dot product test)
- Parallel computing (MPI)
- PML [Grote and Sim, 2010]

Methods:

• Variable projection method

Eliminate the linear variable \boldsymbol{w}

Reduced objective function

• Extended modelling concept

Overcome local minima obstacle

Future work

- VPM in RVL
- Source function estimation in IWAVE
- Reduce computational cost

Thanks to TRIP sponsors and members

- Almomin, A., and B. Biondi, 2013, Tomographic full waveform inversion (tfwi) by successive linearizations and scale separations: Presented at the 75th EAGE Conference & Exhibition-Workshops.
- Golub, G., and V. Pereyra, 2003, Separable nonlinear least squares: the variable projection method and its applications: Inverse problems, **19**, R1.
- Golub, G. H., and V. Pereyra, 1973, The differentiation of pseudo-inverses and nonlinear least squares problems whose variables separate: SIAM Journal on numerical analysis, **10**, 413–432.
- Grote, M. J., and I. Sim, 2010, Efficient pml for the wave equation: arXiv preprint arXiv:1001.0319.
- Rickett, J., 2013, The variable projection method for waveform inversion with an unknown source function: Geophysical Prospecting, 61, 874–881.
- Symes, W. W., 2008, Migration velocity analysis and waveform inversion: Geophysical Prospecting, **56**, 765–790.

Symes, W. W., and M. Kern, 1994, Inversion of reflection seismograms by differential semblance analysis: algorithm structure and synthetic examples1: Geophysical Prospecting, **42**, 565–614.