

Log-validated FWI with wavelet phase and amplitude updating applied on Hussar data

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Introduction

The unknown wavelet represents a challenge that prevents the successful application of FWI on real seismic data. We propose a methodology to correct the amplitude and phase of the modelled data, and with this information, update the wavelet in each iteration.

Methodology

Equation 1 shows how the velocity perturbation δv is obtained when a PSPI gradient is applied:

$$\delta v = \lambda \text{Imp}(\delta R) = \lambda g \quad (1)$$

δR is the pseudo-reflectivity produced by the PSPI migration of the data residuals with a deconvolution imaging condition (equation 2). Imp denotes impedance inversion and λ calibrates the gradient g with well-log information.

$$\delta R = \int \sum_{s,r} \frac{\delta U_r(x, z, \omega) D_s^*(x, z, \omega)}{D_s(x, z, \omega) D_s^*(x, z, \omega) + \mu I_{max}(z)} d\omega \quad (2)$$

where δU_r is the upgoing receiver data residual wavefield, D_s is the downgoing source wavefield, μ is a small stability constant and $I_{max} = \max(D_s D_s^*)$. δU_r can be expressed as the difference between the observed and modelled upgoing wavefields U_o and U_m :

$$\delta U_r(x, z, \omega) = U_o(x, z, \omega) - U_m(x, z, \omega) \quad (3)$$

From the migration of the observed and modelled data we obtain the reflectivity for observed and modelled datasets $R_{o,z}$ and $R_{m,z}$, respectively :

$$R_{o,z} = \int \sum_{s,r} \frac{U_o(x, z, \omega) D_s^*(x, z, \omega)}{D_s(x, z, \omega) D_s^*(x, z, \omega) + \mu I_{max}(z)} d\omega \quad (4)$$

$$R_{m,z} = \int \sum_{s,r} \frac{U_m(x, z, \omega) D_s^*(x, z, \omega)}{D_s(x, z, \omega) D_s^*(x, z, \omega) + \mu I_{max}(z)} d\omega \quad (5)$$

By comparing $R_{o,t}$ and $R_{m,t}$ (in time domain), we have the elements to estimate an amplitude A and a phase ϕ that minimize the cost function in equation 6:

$$\epsilon_R = \sum (R_{o,t} - R_{m,t})^2 \quad (6)$$

The velocity perturbation can be expressed now as:

$$\delta v_t = \lambda \text{Imp}(R_{o,t} - R_{m,t}(A, \phi)) \quad (7)$$

We finally go back to depth to update the velocity model for iteration k . We also use A and ϕ to update the wavelet.

$$m_{k+1} = m_k + \delta v_z \quad (8)$$

Numerical examples

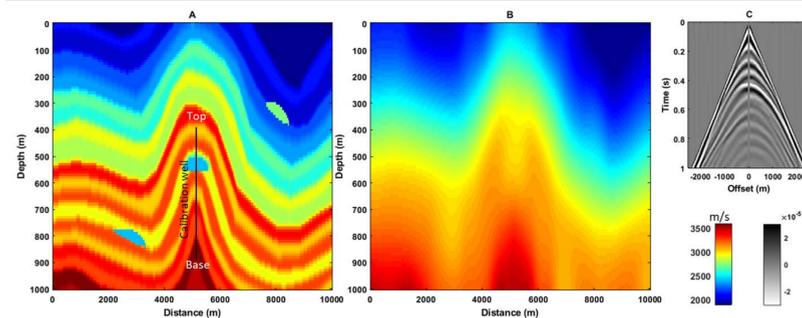


FIG. 1. A) True model and calibration well. B) Initial model. C) Observed shot.

Inversion with wrong wavelet

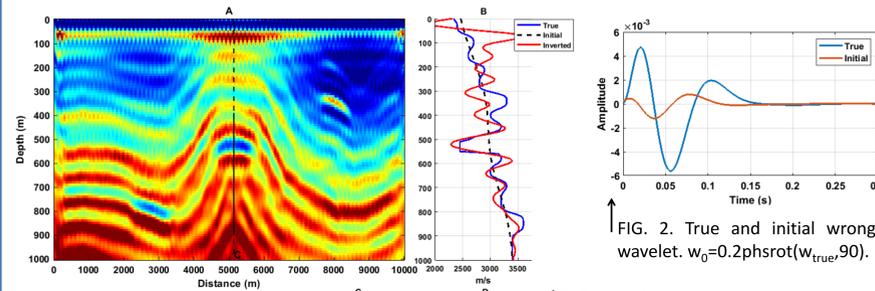


FIG. 2. True and initial wrong wavelet. $w_0 = 0.2 \text{ phsrot}(w_{true}, 90)$.

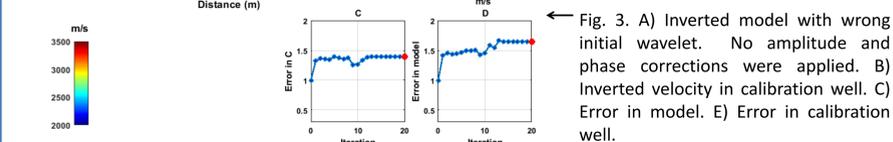


FIG. 3. A) Inverted model with wrong initial wavelet. No amplitude and phase corrections were applied. B) Inverted velocity in calibration well. C) Error in model. D) Error in calibration well.

Inversion applying amplitude and phase updating

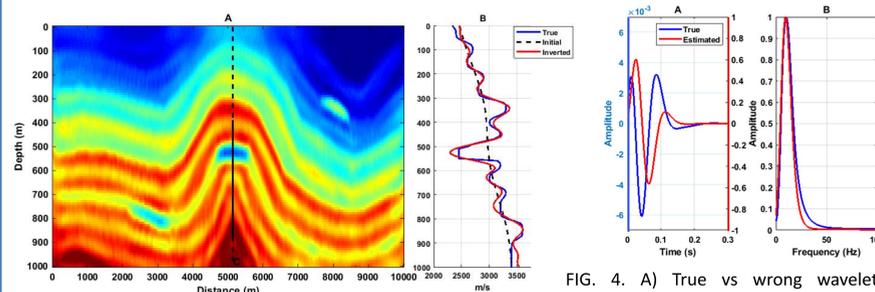


FIG. 4. A) True vs wrong wavelets estimated from the seismic. B) Amplitude spectra.

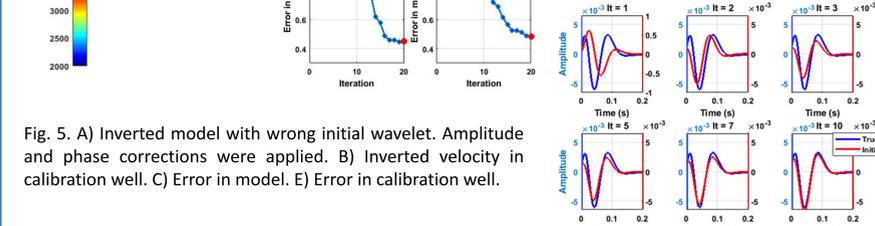


FIG. 5. A) Inverted model with wrong initial wavelet. Amplitude and phase corrections were applied. B) Inverted velocity in calibration well. C) Error in model. D) Error in calibration well.

FIG. 6. Updated wavelet.

Hussar dataset

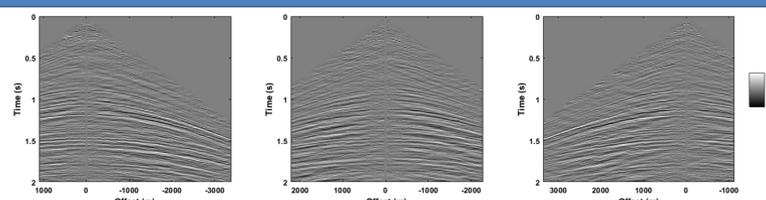


FIG. 7. Example of Hussar's shots used in the inversion.

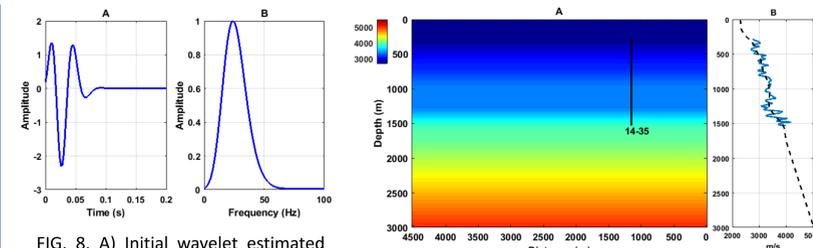


FIG. 8. A) Initial wavelet estimated from the seismic. B) Amplitude spectrum.

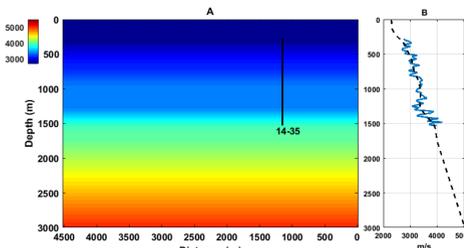


FIG. 9. A) Initial model for Hussar inversion. B) The P-wave velocity in well 14-35 was used to generate the initial model.

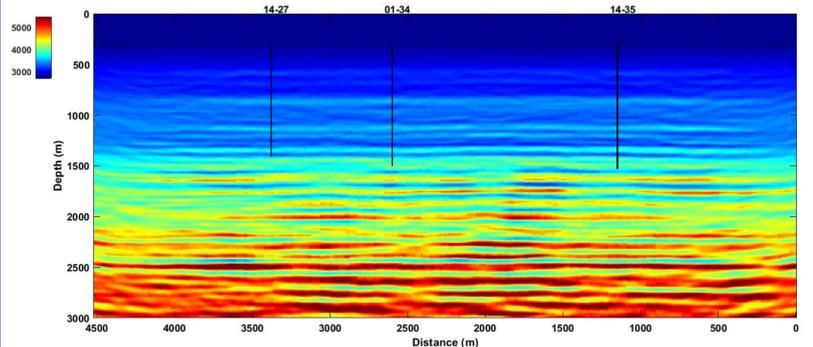


FIG. 10. Inverted model for Hussar dataset.

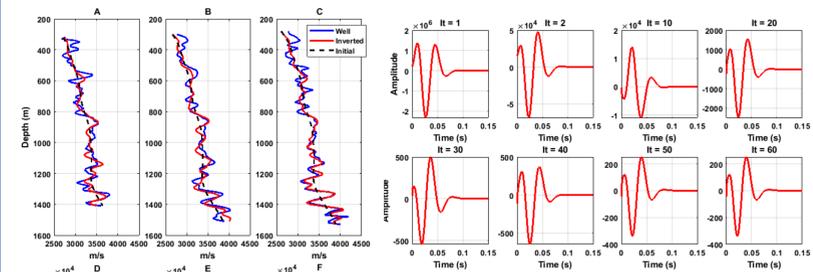


FIG. 11. Evolution of the updated wavelet.

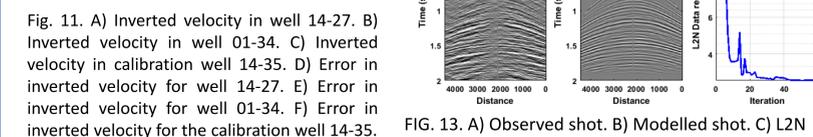


FIG. 12. A) Observed shot. B) Modelled shot. C) L2N of data residuals.

Conclusions

We proposed a methodology to diminish the negative impact that a wrong wavelet produces in FWI. Our methodology consists in separating the migration of the observed and modelled data previous to the construction of the gradient. Through the comparison of these reflectivity datasets in the time domain, we are able to estimate an amplitude and phase correction. We applied this scheme to synthetic data and Hussar dataset obtaining encouraging results. This methodology seems to be robust enough to be applied to real data; however, there is still much to do in order to find the optimum wavelet.

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