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Internal Multiple Prediction - A New Approach Based on Seismic Interferometry and Marchenko Autofocusing

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SUMMARY

Standard seismic processing steps such as velocity analysis and reverse time migration (imaging) usually assume that all reflections are primaries: multiples represent a source of coherent noise and must be suppressed to avoid imaging artefacts. Suppressions methods are relatively ineffective for internal multiples. We show how to predict and remove internal multiples using Marchenko autofocusing and seismic interferometry. We first show how internal multiples can theoretically be reconstructed in convolutional interferometry by combining purely reflected, up- and down-going Green’s functions from virtual sources in the subsurface. We then generate the relevant up- and down-going wavefields at virtual sources along discrete subsurface boundaries using autofocusing. Then, we convolve purely scattered components of up- and down-going Green’s functions to reconstruct only the internal multiple field which is adaptively subtracted from the measured data. Crucially, this is all possible without detailed modelled information about the Earth’s subsurface. The method only requires surface reflection data and estimates of direct (non-reflected) arrivals between subsurface sources and the acquisition surface. The method is demonstrated on a stratified synclinal model and is particularly robust against errors in the velocity model used.
Introduction

Many standard seismic data processing steps use the single-scattering Born approximation, and therefore require that multiples are removed from data in advance to avoid errors. Surface related multiples particularly impact on seismic images resulting from marine data, and much effort has been devoted to their removal (see review by Dragoset et al., 2010). Internal multiples strongly affect land data, and relatively fewer techniques exist to predict and remove them from reflection data.

Jakubowicz (1998) used combinations of three observed reflections to predict and remove multiples, leading to several other variations on that theme (e.g., Hung and Wang, 2012). However, these schemes require significant prior information about subsurface reflectors or reflections prior to multiple prediction. Inverse scattering methods for multiple prediction (e.g., Weglein et al., 1997, 2003) do not demand so much information but tend to be relatively computationally expensive.

Seismic interferometry techniques synthesise Green’s functions between real source or receiver locations by integrating cross-correlations or convolutions of wavefields recorded by receivers or emanating from sources located elsewhere (Wapenaar and Fokkema, 2006). Marchenko autofocusing estimates up- and down-going components of Green’s functions between virtual source locations inside a medium and real receivers at the surface (Broggini et al., 2012; Wapenaar et al., 2012).

Here we present a new method that creates multiple-free data combining interferometric and autofocusing methods.

Method and Theory

Convolutional interferometry uses acoustic reciprocity theorems to express the Green’s function between two locations (Van Manen et al., 2005, Wapenaar and Fokkema, 2006):

\[
G(x_2, x_1) \approx \int_S \frac{2j\omega}{c(x)\rho(x)} \{G(x_2, x)G(x_1, x)\} dS
\]

Here \(\rho(x)\) denotes density, \(c(x)\) denotes velocity, \(x_1\) and \(x_2\) are two receiver (source) positions, \(G(x_2, x_1)\) represents the frequency domain Green’s function recorded at \(x_2\) for an impulsive source at \(x_1\), and \(S\) is an arbitrary boundary of sources (receivers) enclosing either \(x_1\) or \(x_2\), (Figure 1(a)).

The main contributions to the evaluation of these integrals come from neighbourhoods of stationary points (Snieder et al., 2006). For some example internal (primary or multiple) reflections, these points are indicated in Figures 1(b) and 1(c). These points are located inside the medium, and usually the corresponding Green’s functions in the integrand \(G(x_1, x)\) and \(G(x_2, x)\) are not available. Nevertheless, autofocusing estimates all such Green’s functions and their up- and down-going components at points \(x\) (Figures 1(d)), given only surface reflection data and an estimate of the direct (non-reflected) wavefield from \(x\) to the surface (Broggini et al., 2012; Wapenaar et al., 2012).

Figure 1(b) and 1(c) illustrate how primary and internal multiple reflections are reconstructed in convolutional interferometry: equation (1) pieces together and integrates energy travelling upwards and downwards from around each stationary point, to calculate energy that would travel along each full ray path. The number of reflections (or scattering order) undergone by an event associated with \(G(x_2, x_1)\) is equal to the sum of the number of reflections undergone by its constitutive components, i.e. \(G(x_1, x)\) and \(G(x_2, x)\). Thus, one component of primaries (scattering order = 1) must be a direct wave (Figure 1(b)); in contrast, internal multiples can be constructed from reflected waves alone, provided that part of the integration boundary lies between the reflecting interfaces (Figure 1(c)).

This difference can be used to estimate the internal multiple wavefield. If we remove the direct waves from the Green’s functions \(G(x_i, x)\), and use an appropriately restricted integration boundary (e.g., the
neighbourhood of each stationary point indicated by a square on $S_2$ in Fig. 1(d)), equation (1) only constructs internal multiples since no direct waves are involved in the process.

Here we consider partial boundaries consisting of horizontal lines (Figures 1(d)) and purely scattered Green’s functions (without direct waves), decomposed into up- and down-going components. Two combinations of up- and down-going Green’s functions construct the internal multiple shown (those around the stationary black and white squares in Figure 1(d)). We therefore revise equation (1) using opposite signs for different combinations:

$$G_{IM}(x_2,x_1) \approx \int_{S_i} \frac{2j\omega}{c(x)\rho(x)} \left\{ G_u^S(x_2,x)G_d^S(x_1,x) + G_d^S(x_2,x)G_u^S(x_1,x) \right\}dS$$

(2)

where $G_{IM}$ stands for the Green’s function’s internal multiple components, $G_u^S$ and $G_d^S$ are up and down-going components of reflected (scattered) Green’s functions that are created using autofocusing, and $S_i$ is a partial boundary ($i=1,2,...$, see Figure 1(d)). Each boundary $S_i$ generates only the multiples whose components $G_u^S$ and $G_d^S$ meet at stationary points along $S_i$, and thus it requires as many boundaries as there are interfaces in the subsurface.

We thus derive an algorithm to estimate internal multiples only:

1) Choose a horizontal boundary $S_i$ in the subsurface. Locate virtual sources at locations $x$ along this line, and compute corresponding up- and down-going Green’s function $G_{ud}(x_p,x)$ using autofocusing, where locations $x_p$ span the surface array.
2) Mute direct waves in the Green’s functions $G_{ud}(x_p,x)$ to produce $G_{ud}^S(x_p,x)$.
3) Apply equation (2) to predict internal multiples $G_{IM}(x_q,x_r)$ for all $x_q,x_r$ in the surface array.

We repeat the procedure using $S_i$ located at different depths, and then stack the results.

Figure 1 (a) Geometrical configuration for convolutional interferometry. Triangles are receivers, stars are sources. (b) and (c): distribution of stationary points for primary and internal multiple reflections, respectively. Circles indicate points $x$ involving direct and scattered waves, squares indicate points involving only scattered waves. The scattering order of $G(x_1,x)$ and $G(x_2,x)$ is indicated between brackets for the various stationary points. (d) No stationary point involving purely scattered waves is located along the partial boundary $S_i$. White and black squares indicates the stationary point along the partial boundary $S_2$ involving different combination of up- and down-going or down- and up-going waves in $G(x_1,x)$ and $G(x_2,x)$, respectively.
Numerical Example

We test the algorithm using a 2-dimensional varying density, constant velocity (v=1500 m/s) synclinal model (Figure 2(a)). Arrays of 201 co-located sources and receivers span 3 km at the top of the model (Figure 2(a)). To test our method’s, we compute direct wave travel times through a medium of incorrect constant velocity (1650 m/s). Crosses in Figure 2(b) correspond to virtual source positions, spanning a total of 9 boundaries S1 to S9 with 120 virtual sources each.

Figure 3(a) shows the reflection data from source 101 indicated in Figure 2, while Figure 3(b) shows estimated primaries obtained by adaptively subtracting (Fomel, 2009) the multiples predicted by stacking results from boundaries S1 to S9 (Figure 3(c)). The 7 primaries are indicated by dashed lines in Figure 3. Six out of the 7 primaries are clearly not reproduced in (c). The primary corresponding to the 5th reflector (black arrow in Figure 3) seems to be predicted (faintly) as a multiple; this is not an error: in this case a multiple has exactly the same kinematics as a primary, and is correctly reconstructed by the method. All internal multiples are predicted by the algorithm in panel (c).

Figure 2 2D constant velocity/varying density model. The black arrow in (a) indicates source number 101 used in subsequent figures. (b) Smooth density model used in equations.

Figure 3 (a) Reflectivity corresponding to source 101 in Figure 2(a). Dashed red lines are superimposed on the 7 primary reflections. Black arrow indicates the primary corresponding to the 5th interface. A time-varying gain has been applied to enhance later portions of the data. (b) Estimated primaries. (c) Internal multiples predicted using boundaries S1 to S9 in Figure 2(b).
We finally applied RTM to the observed data and to the demultiplied data. The images are shown in Figure 4 (only the lower part of the model is shown). Internal multiples, if not attenuated prior to migration, result in many artefacts (as indicated by red arrows in the left portion of Figure 4) contaminating the image. RTM of demultiplied data provides a much cleaner image, with considerably fewer and low amplitudes artefacts (black arrows in the right portion of Figure 4). Actual reflectors are comparably well imaged by the two methods (blue arrows in Figure 4).

Conclusions

We have presented a new, automated, relatively cheap method to predict internal multiples based on autofocusing and convolutional interferometry. The method was demonstrated on acoustic data and proved to be stable with respect to inaccuracies in the autofocused Green’s functions.

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![Figure 4](image_url)

Figure 4 (a) RTM Image obtained migrating the recorded data (primaries and internal multiples). (b) RTM image obtained migrating the predicted primaries. Blue arrows indicate actual reflectors; red and black arrows indicate artefacts in the conventional and the primary RTM image, respectively.

References