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Internal multiple adaptive subtraction using Huber norm

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ABSTRACT

There are two steps in internal multiple elimination, the first step is multiple prediction (predicted multiple model by inverse scattering series (ISS) method from marine seismic data only), the second step is adaptive matching subtraction, subtract multiple from seismic data. Because of the complex generation mechanism of internal multiple, the second step is always the main challenge of internal multiple suppression. A new subtraction method using Huber norm is proposed to remove internal multiples in this paper, it can deal with the negative influence of amplitude and phase in internal multiple subtraction. In this approach, the multi-channel Huber norm function minimized by quasi-Newtonian method that has the potential for more accurate and robust multiple subtraction. Tests with synthetic and field data suggest that internal multiple adaptive subtraction using the Huber norm gives highly satisfactory result, and shows its effectiveness.

1. Introduction

Pattern-based multiple attenuation methods include Radon transform method, frequency–wavenumber spectrum (FK) method and predictive deconvolution, which have been used for internal multiple suppression (Liu et al., 2014). However, the inverse scattering series (ISS) method (Carvalho et al., 1992; Weglein et al., 2006) is a commonly used algorithm for suppressing internal multiples based on wave equation without any pattern information. There are two steps: multiple prediction and adaptive subtraction. In the first step, ISS uses first-order Born approximation to predict internal multiples. The method does not require any information about the subsurface, but the amplitude and phase of predicted multiple model is very different from real multiple (Luo et al., 2011). In the second step, usually a real seismic trace is used to construct filters that match the predicted multiple model and field data. The predicted multiple model then has the same amplitude and phase after matching filtering, thus helping to remove internal multiples (Araújo, 1994; Berkhout, 1997; Ikelle et al., 2002; Cao and McMechan, 2011). Traditional matching filters are always calculated by a residual minimized algorithm in L_2-norm or L_1-norm (Chapman and Barrodale, 1983; Guitton and Verschuur, 2004; Fomel, 2009; Wang et al., 2009; Ventosa et al., 2012). However, when the internal multiple strongly interferes with primary energy, these methods are difficult to deal with internal multiple subtraction (Luo et al., 2007).

There are two factors affecting the matching result. The first factor is amplitude treatment, the energy of the real internal multiple is a lot weaker than primary because internal multiples are generated by downward reflection in seabed, a lot of seismic wave energy is transmitted, but only little energy is saved to be reflected and generate internal multiple. In this situation, matching residual minimize by L_2-norm will cause the primary to be matched with multiple model prediction, but not with real internal multiples. In this case, it is preferable to choose L_1-norm to minimize the matching residual, but the L_1-norm is insensitive to large noise of seismic data (Guitton and William, 2003).

The second factor is orthogonality problem. When multiple phase is different from the primary less than 1/4-phase, it is difficult to distinguish each other, since the move-outs of the internal multiple are always fairly close to primary' (Xie, 2013). Therefore, for these reasons, a new method of internal multiple subtraction is needed.

The Huber norm is a robust method between smooth L_2-norm treatment with small residuals and robust L_1-norm treatment with large residuals (Huber, 1973). Because the noise is always accompanied by seismic data acquisition, most of internal multiple-matching filters are generally ill-posed. Noise-sensitive method of L_2-norm will not be stabilized enough in internal multiple matching filtering (Claerbout and Muir, 1973; Taylor et al., 1979; Scales and Gersztenkorn, 1987). The residual minimized with L_1-norm method is not smooth enough, also it is quite stabilized in matching filtering. Previously reported methods in dealing with this problem have suggested that a lot of attentions are given to "small residuals only", but this approach may not be appropriate in large data-match filtering in internal multiple adaptive subtraction. Clearly, in this case, we need a new method both smooth and robust.

In the present work, we present Huber norm filtering in internal multiple subtraction, which greatly improved both the stability and accuracy of traditional subtraction algorithm.

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2. Inverse scattering series internal multiple prediction method

The first step of ISS internal multiple elimination method is to predict the internal multiple model using inverse scattering series (Weglein et al., 2003). The ISS internal multiple prediction algorithm was found through a combination of simple scattering models, some forward scattering series is constructed by summing certain types of scattering interactions which represent one first order approximation internal multiple, add all interactions of this type to construct the internal multiple model, so it is a data-driven algorithm without any velocity configuration. Its matrix notation is:

$$G_{In} = \sum_i G_0^d V_i G_0^d V_{n-i+1} G_0^d \qquad (i = 1, 2, 3, \cdots), \tag{1}$$

where G_0^d is the free space Green function, V_i is the scattering-off perturbation, and G_{In} is the predicted internal multiple model. All first-order internal multiples begin to create scattering series with three reflection-like (octagonal) scatterings. The mathematical and algorithmic relationship has a low–high–low configuration, the piece of this term representing the first order approximation to an internal multiple is exactly one for which the seismic wave scattering satisfy internal multiple' wave path as Fig. 1. This reflection condition allows a unique internal multiple model to be found. Once all relationships in this form are exhausted, they are summed to obtain the real internal multiple model.

The ISS internal multiple prediction 2D algorithm (Weglein et al., 2009) is written as:

$$b_{3IM} = \int dx_g \int_{-\infty}^{+\infty} dz_1 b_1\left(x_s, x_g, z_1\right) e^{ikz_1} \int_{-\infty}^{z_1-\varepsilon} dz_2 b_1\left(x_s, x_g, z_2\right) e^{-ikz_2} \int_{z_2+\varepsilon}^{+\infty} dz_3 b_1\left(x_s, x_g, z_3\right) e^{ikz_3}, \tag{2}$$

where x_s,x_g are the horizontal wavenumbers of the receivers and sources, respectively; $b_1(x_s,x_g,z_1)$ is the uncollapsed migration incident plane-wave data in the frequency domain; and $z_i(i = 1,2,3)$ is the pseudo-depth. Then, b_{3IM} is transformed back to the space-time domain. Then all first-order internal multiples are predicted.

3. Multi-channel adaptive subtraction based on Huber norm

The ISS method thus creates an internal multiple model with exact time and amplitude information. In order to suppress internal multiples, we need to subtract matched multiples from the original data using the Huber norm. This is the second step in internal multiple attenuation, which is given by:

$$e(t) = |d(t) - \alpha(t) * m(t)|_{Huber} = |r|_{Huber} = \sum N_\varepsilon(|r_i|), \tag{3}$$

where $d(t)$ is the real seismic data, $m(t)$ is the predicted multiple model, $\alpha(t)$ is a matching factor, and $N(r)$ is the total residual of matching subtraction. When the error parameter r_i approaches the threshold parameter ε, $|r|_{Huber}$ oscillates between L_2-norm and L_1-norm for different iterations. This is shown in Fig. 2, where the upper (broken) line shows the L_1-norm magnitudes and the lower (solid) line shows the L_2-norm magnitudes.

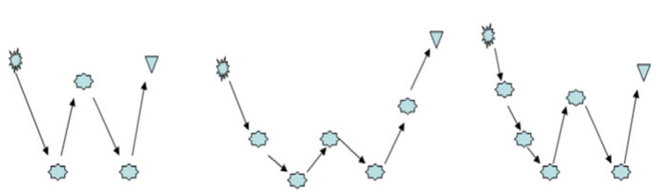

Fig. 1. Diagrams corresponding to different classes of internal multiple scattering.

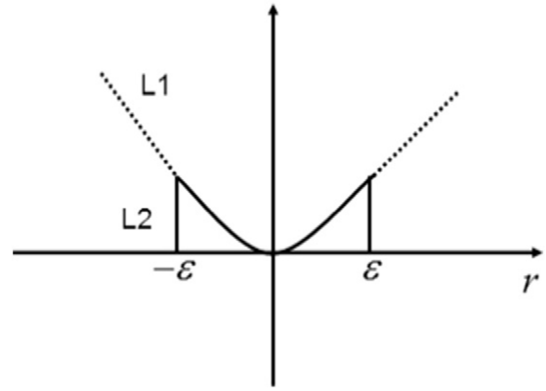

Fig. 2. Error magnitudes proposed by Huber norm (Huber, 1973).

For the internal multiple matching filter, the reconstruction error function is given by:

$$e(t) = |d(t) - \alpha(t) * m(t)|_{Huber} = ||w(d(t) - \alpha(t) * m(t))||^2, \tag{4}$$

where $W = diag\left(\frac{1}{(1+r_i^2/\varepsilon^2)^{1/4}}\right)$; $d(t)$ is the original data containing the internal multiple; and $\alpha(t)$ and $m(t)$ are defined as for Eq. (3). Considering the orthogonality of the matching filter, a multi-channel matching filter may be rewritten $\alpha(t) = (\alpha_1, \alpha_2, \alpha_3 \text{ L } \alpha_n)$. The predicted multiple model is then given by:

$$m(t) = \begin{pmatrix} m(1) & 0 & \cdots & 0 \\ m(2) & m(1) & \cdots & 0 \\ m(3) & m(2) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ m(\text{n}) & m(n-1) & \cdots & m(n-l+1) \end{pmatrix}. \tag{5}$$

For residual minimization, the objective function may be solved by the conjugate-gradient method, the Levinson algorithm or by Newtonian methods. Assuming that the partial derivative of $\alpha(t)$ is continuous, then:

$$\alpha = \frac{M^T W^T W d}{M^T W^T W M} \tag{6}$$

where M and W have been defined in Eqs. (4) and (3), M^T and W^T are transposed matrix of M and W respectively.

Consequently, by taking the Huber norm, and introducing the L-BFGS optimization algorithm into the matching filter operator calculation, a faster, more accurate matching method is obtained.

4. Numerical test

Fig. 3 shows a synthetic shot gather obtained from a four-layer horizon velocity model using the finite difference method and assuming a free absorbing boundary. The shot interval is 20 m, receiver interval 10 m, data sampling rate is 2 ms and wavelet frequency is 25 Hz. The data contains primary and internal multiples only (Fig. 3(b)); seismic events from 1 to 4 are primary, and the remainder is internal multiples. Fig. 3(c) is the result of traditional subtraction. Fig. 3(d) is the Huber norm matching the filter subtraction result. It is clear that Fig. 3(c) shows some residual multiples. Fig. 3(d) is the synthetic shot gather after multiple subtraction, it looks much better than Fig. 3(c).

To demonstrate the approach of internal multiple subtraction in horizontal mode, Fig. 4(a) shows the velocity model, with half of the layers being horizontal and the other half being oblique. The velocity reversal is more complex. Fig. 4(b) is the acoustic finite-difference forward-