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Least-squares reverse time migration with and without source wavelet estimation

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ABSTRACT

Least-squares reverse time migration (LSRTM) attempts to find the best fit reflectivity model by minimizing the mismatching between the observed and simulated seismic data, where the source wavelet estimation is one of the crucial issues. We divide the frequency-domain observed seismic data by the numerical Green's function at the receiver nodes to estimate the source wavelet for the conventional LSRTM method, and propose the source-independent LSRTM based on a convolution-based objective function. The numerical Green's function can be simulated with a dirac wavelet and the migration velocity in the frequency or time domain. Compared to the conventional method with the additional source estimation procedure, the source-independent LSRTM is insensitive to the source wavelet and can still give full play to the amplitude-preserving ability even using an incorrect wavelet without the source estimation. In order to improve the anti-noise ability, we apply the robust hybrid norm objective function to both the methods and use the synthetic seismic data contaminated by the random Gaussian and spike noises with a signal-to-noise ratio of 5 dB to verify their feasibilities. The final migration images show that the source-independent algorithm is more robust and has a higher amplitude-preserving ability than the conventional source-estimated method.

1. Introduction

LSRTM, similar to the full waveform inversion (FWI), attempts to minimize the misfit between the observed and simulated data by an iterative algorithm to refine seismic images towards the true reflectivity (Dong et al., 2012; Zeng et al., 2014). Therefore, LSRTM can produce migration images with better quality than conventional migrations (Ji, 2009; Dai et al., 2012, 2013; Luo and Hale, 2014; Dutta and Schuster, 2014; Zhang and Schuster, 2014; Tan and Huang, 2014a; Aldawood et al., 2015; Wong et al., 2015; Y. Zhang et al., 2015) by removing migration artefacts, improving the illumination and revealing more subsurface details. Furthermore, LSRTM is currently the only effective way to directly migrate the blended seismic data from simultaneous-source acquisition which becomes more and more appealing for its tremendous acquisition cost reduction and the quality improvement of the seismic data (Chen et al., 2015). It can be conducted both in the time and frequency domains (Dai et al., 2013; Ren et al., 2013) for the isotropic and anisotropic (Dai et al., 2012) or the acoustic and visco-acoustic (Dutta and Schuster, 2014; Li et al., 2016) media.

However, LSRTM encounters the problems similar to FWI. The primary problems are the great computation cost and memory requirement. Fortunately, many methods, e.g., source-encoding method (Dai et al., 2012, 2013; Zhang et al., 2013; Chen et al., 2015), plane-wave method (Dai and Schuster, 2013; Li et al., 2014) and boundary-wavefield extrapolation method (Tan and Huang, 2014b; Zhang et al., 2014), have been developed to solve these two problems. In addition, the preconditioning (Dai et al., 2011; Liu et al., 2013) and regularization (Xue et al., 2016) methods are usually utilized to accelerate the convergence rate of LSRTM, by which the iteration numbers can be efficiently reduced.

Besides the problems of memory requirement and computation cost, the actual source wavelet is difficult to extract from practical seismic data and the incorrect wavelet would contaminate the migration images (Kim et al., 2011, 2013; Tang and Wang, 2012) or inversion results (Song et al., 1995; Yuan and Wang, 2011; Luo et al., 2014). Conventional LSRTM supposes that the source wavelet is known beforehand. However, an incorrect source wavelet would produce some artefacts to the migration images, such as polarity reversal and layer dislocation. To solve the problem of source wavelet, several techniques are usually adopted in FWI, e.g., the iterative estimation of source signature (IES) method (Song et al., 1995), the deconvolution-based method (Lee and Kim, 2003; Zhou et al., 2014), and the convolution-based method (Choi and Alkhalifah, 2011; Zhang et al., 2015b, 2016). With regard to the migration, Kim et al. (2011) proposed the frequency-domain source estimation method using optimization technique for reverse time migration (RTM). Kim et al. (2013) developed the source estimation idea to the time-domain RTM by the deconvolution method. Tu et al. (2013) performed the least-squares migration (LSM) with source

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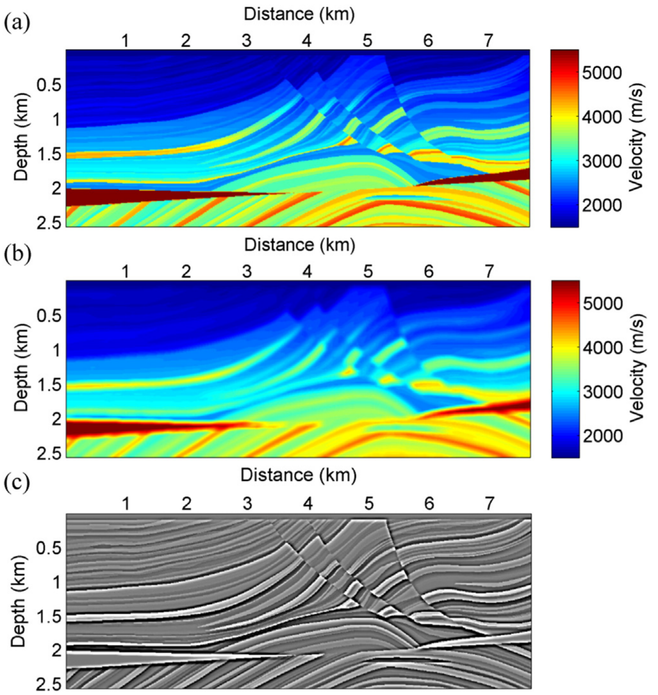

Fig. 1. (a) The true Marmousi velocity model, (b) the smoothed (or migration) velocity model, and (c) the corresponding true reflectivity model.

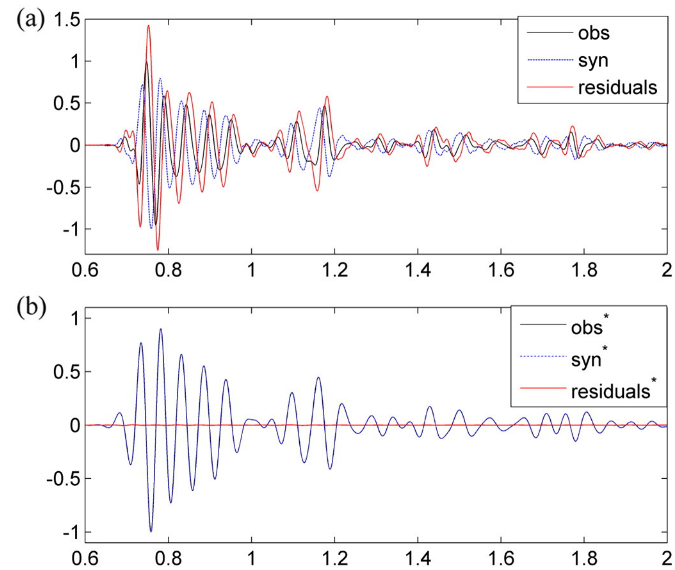

Fig. 3. Trace 300 of the 20th source at X = 2 km chosen from: (a) the conventional observed (solid black line) and simulated (dashed blue line) seismograms, (b) the convolution-based observed (solid black line) and simulated (dashed blue line) seismograms. The red line denotes the residuals between the observed and simulated seismograms. The superscript of asterisk represents the convolution-based method. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

estimation by the generalized variable projection method. Due to the similarity of FWI and LSRTM, the techniques for solving the source problem used by FWI can also be used by LSRTM.

In this paper, we propose the time-domain source-independent (without source estimation) LSRTM (Zhang et al., 2015a) based on the convolution-based objective function to suppress the artefacts caused by the incorrect source wavelet, and then make a comparison with the deconvolution-based source estimation method for conventional LSRTM. The hybrid-norm objective function is applied to improve the robustness of both methods. Synthetic data with and without noises are used to verify the advantages of the source-independent algorithm compared to the conventional source-estimated method.

The rest of this paper is organized as follows. First, we review the theory of the conventional LSRTM, and then give an introduction to the deconvolution-based source estimation method and the convolution-based source-independent method. Second, we use the synthetic data generated with the Marmousi model to verify the feasibilities of both the algorithms and make a sensitivity analysis to the source wavelet phase for the source-independent method. Finally, we give the discussions and draw some conclusions.

2. Theory

2.1. Conventional LSRTM

We review the theory of LSRTM (Dai et al., 2012, 2013) by the acoustic wave equation with a constant density

$$\frac{1}{c_0(\mathbf{x})^2}\frac{\partial^2 p_0(\mathbf{x},t;\mathbf{x}_s)}{\partial t^2}-\nabla^2 p_0(\mathbf{x},t;\mathbf{x}_s)=s(t;\mathbf{x}_s), \tag{1}$$

where $\mathbf{x}_s$ denotes the source location, $p_0(\mathbf{x},t;\mathbf{x}_s)$ is the background wavefield associated with the background (migration) velocity model $c_0(\mathbf{x})$ and the source wavelet $s(t;\mathbf{x}_s)$. A perturbation $\delta c(\mathbf{x})$ in the velocity model $c(\mathbf{x})=c_0(\mathbf{x})+\delta c(\mathbf{x})$ will generate a perturbation $\delta p(\mathbf{x},t;\mathbf{x}_s)$ in the wavefield $p(\mathbf{x},t;\mathbf{x}_s)=p_0(\mathbf{x},t;\mathbf{x}_s)+\delta p(\mathbf{x},t;\mathbf{x}_s)$. In the following text, we use $q(\mathbf{x},t;\mathbf{x}_s)$ to represent $\delta p(\mathbf{x},t;\mathbf{x}_s)$. Based on the Born approximation, we can obtain the equation for the wavefield perturbation $q(\mathbf{x},t;\mathbf{x}_s)$

$$\frac{1}{c_0(\mathbf{x})^2}\frac{\partial^2 q(\mathbf{x},t;\mathbf{x}_s)}{\partial t^2}-\nabla^2 q(\mathbf{x},t;\mathbf{x}_s)=\frac{1}{c_0(\mathbf{x})^2}m(\mathbf{x})\frac{\partial^2 p_0(\mathbf{x},t;\mathbf{x}_s)}{\partial t^2}, \tag{2}$$

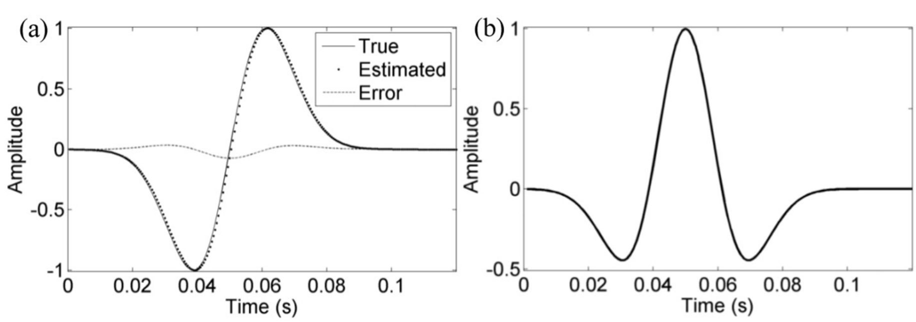

Fig. 2. (a) The true source wavelet (solid line) generated by the first derivative of Gaussian function, the estimated wavelet (dotted line), and the estimated errors (dashed line). (b) The incorrect source wavelet generated by the second derivative of the Gaussian function. Both of them have a dominant frequency of 20 Hz.