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Model-driven Deep Learning Nonstationary Seismic Reflectivity Inversion Method

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Summary

Nonstationary reflectivity inversion methods become more and more attractive, which can directly invert the reflectivity from the nonstationary field data to improve the resolution. However, the approach needs to pre-estimate the time-varying wavelets, design the regularization terms, and pre-determine the regularization parameters. In addition, the computational cost is generally expensive for the field application. To alleviate these limitations, we proposed a model-driven deep learning method to implement blind nonstationary deconvolution. We start from the alternating iterative algorithm to derive the iterative solutions of the blind deconvolution, and apply the convolutional neural networks to replace the gradient components. Then, a model-driven deep neural network is built by mapping each iteration into one layer to estimate the reflectivity and time-varying wavelets simultaneously. To alleviate the requirement of the training datasets, we adopt a semi-supervised training strategy by introducing a data-consistency loss. Finally, a synthetic data example is conducted to validate the proposed method.

Introduction

Seismic reflectivity inversion, also called deconvolution, has been an essential part of seismic exploration, and it improves the resolution of seismic data to characterize the reservoir structure and calculate the reservoir parameters to identify reservoirs. In reality, the field data is nonstationary because of the heterogeneous, anisotropic, and anelastic mediums. This paper primarily discusses the nonstationary case caused by anelastic attenuation and dispersion. In this case, the seismic wavelet is time-varying with amplitude loss and phase rotation. There are generally two distinct classes of seismic reflectivity inversion methods to mitigate the effect of time-varying wavelets, i.e., two-step method and direct implementations of nonstationary reflectivity inversion. For the first category, the first step is to apply the inverse Q filtering to obtain stationary seismic trace, and then the classical reflectivity inversion method can be involved to estimate the reflectivity. Direct implementation of nonstationary reflectivity inversion is based on a time-varying convolution model to directly extract the reflectivity from the nonstationary trace. There are usually some limitations for these non-learning methods, for instance, pre-estimating accurate Q values or seismic source wavelet.

More recently, deep learning methods show a great learning ability to solve inverse problems, and it has been applied to solve some seismic inversion problems. According to the labeled data requirements, there are three primary deep learning methods, i.e., supervised learning, semi-supervised learning, and unsupervised learning. In the case of enough labeled data, supervised learning can usually obtain high-accuracy inversion results. However, obtaining high-quality labeled data is difficult because of the complex field data environment. Semi-supervised and unsupervised learning methods are attractive to circumvent the requirement of a large number of labeled data. Unsupervised learning method can be used to learn a mapping by using the unlabeled data. Semi-supervised learning methods are the middle methods to utilize few labeled and large unlabeled data.

In this paper, we propose a model-driven deep learning method to perform the blind nonstationary seismic reflectivity inversion to simultaneously recover the reflectivity and time-varying wavelets, which extends the work of Chen et al. (2021). Specifically, based on the nonstationary convolution model, we start from the model-based inversion approach to derive four iterative solutions, in which the convolutional neural networks are used to replace the gradient components, and the hyper-parameters in the solutions are treated as the weights of the network. Finally, a deep neural network is built by unrolling the derived alternating iterative solutions. We adopt a semi-supervised learning strategy by adding a data-consistency loss associated with the unlabeled data to transfer the knowledge and avoid over-fitting.

Theory

The seismic data is usually nonstationary, which can be modeled as

$$s(t) = w(t,\tau) \odot r(t) + n(t), \tag{1}$$

where t is time, and symbols $\odot$ denotes the nonstationary convolution. Signal $s(t)$ indicates the nonstationary seismic trace, $r(t)$ represents the reflectivity, $n(t)$ represents the random noise, and $w(t,\tau)$ indicates the time-varying wavelet, which is related to the attenuation model. To solve this problem, we approximate equation 1 by using windows (Margrave et al., 2011; Lari and Gholami, 2019) to alleviate the instability and uncertainty of the inversion solution,

$$\mathbf{s} \approx \sum_{j=1}^{B} \mathbf{w}_j * [\mathbf{r}\Omega_j] + \mathbf{n}, \tag{2}$$

where $\mathbf{s}$, $\mathbf{r}$, and $\mathbf{n}$ denote the vectors of seismic trace, reflectivity, and random noise, respectively. $\mathbf{w}_j$ denotes the vector of the time-varying wavelet at the jth window, Ω_j represents the function of the window, centered at time $t = t_j$, and B denotes the number of windows. The set of windows is called a partition of unity (POU) and has the property that $\sum_{j=1}^{B} \Omega_j = 1$.

To invert the reflectivity from equation 2, we establish the following cost function in the case of unknown $\mathbf{w}_j$,

$$J = \min_{\mathbf{r},\mathbf{w}} \frac{1}{2} ||\mathbf{s} - \sum_{j=1}^{B} \mathbf{w}_j * [\mathbf{r}\Omega_j]||_2^2 + \lambda\Psi(\mathbf{r}) + \mu\Phi(\mathbf{w}), \tag{3}$$

where $\mathbf{w}$ is a set of time-varying wavelets by combining all wavelets at each window, and thus it is a matrix. Symbols Ψ and Φ denote the regularization terms which encode the prior information about $\mathbf{r}$ and $\mathbf{w}$ and penalize unfeasible solutions. There are primarily three limitations to this optimization algorithm. One is that the setting of initial values affects the convergence and accuracy; second is that the optimization algorithms are usually computationally demanding; last is that the explicit form of regularization terms and the sensitive parameters are needed to be predetermined, which limit the type of prior information and the inversion accuracy. Therefore, we try to introduce the deep neural network to alleviate the limitations of the above model-driven method. To derive the deep neural network, we split the problem in equation 3 into two subproblems, and then we can obtain four iterative solution forms by using the half-quadratic splitting (HQS) algorithm. We use the convolutional neural network to replace the gradient components in the solutions, similar to the work of Chen et al. (2021). Finally, a model-driven deep neural network architecture is built by unrolling the iterative solutions, as shown in Figure 1. In this figure, the inverse model includes two alternative components, i.e., yellow and orange modules used to invert the time-varying wavelets and reflectivity.

$\mathbf{x}^k$ and $\mathbf{z}^k$ are the introduced auxiliary variables during solving; $\mathbf{w}^k$ and $\mathbf{r}^k$ indicate the estimated time-varying wavelets and reflectivity. They correspond to the derived iterative solutions. Here, we adopt a semi-supervised mean square loss function to optimize this network.

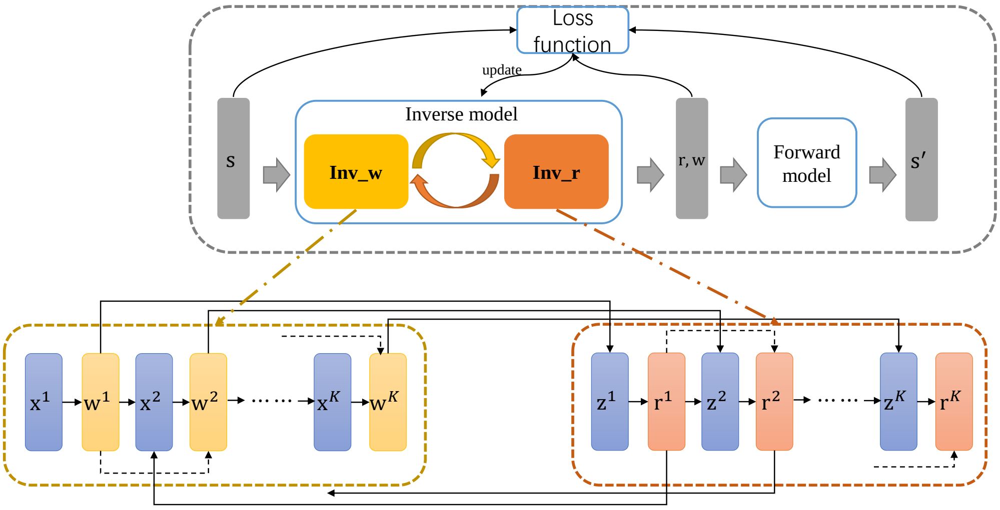

Figure 1: Proposed model-driven deep neural network and semi-supervised learning flow.

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Example

Marmousi II model is a classical geological model used in many papers to validate imaging. We select this resampled model as a case study to validate our proposed deep learning method. Figure 2a shows the synthetic nonstationary data. Figure 2b shows the reflectivity model obtained by the vertical incidence reflectivity formula. Then, a Ricker wavelet with 30 Hz dominant frequency and 45^0 phase rotation is set as the source wavelet. We generate Figure 2a by inputting the Q model, reflectivity, and source wavelet into a nonstationary convolution model. Finally, we add some Gaussian noise into the synthetic data to generate noisy data with a signal-to-noise ratio (S/N) of 25 dB. This noisy dataset has 551 time sampling points and 1361 traces, and it is treated as a predicted dataset to validate our proposed method. For this predicted data, there are 10 labeled data; that is, we select ten evenly traces as the labeled data and the remaining traces of data as the unlabeled data. To validate our proposed method, we compare it with the non-learning blind deconvolution method proposed by Lari and Gholami (2019). Figure 2c and 2d show the estimated reflectivity profiles by using the proposed deep learning and non-learning methods, respectively. It can be seen that the inversion reflectivity profile in Figure 2c is better than that in Figure 2d. Specifically, the details and energy relationships are recovered better in Figure 2c. In comparison, there are details loss and incorrect energy relationships in Figures 2d. To quantitatively analyze the inversion results, we calculate the PCCs between the inverted reflectivity coefficients and the true reflectivity to be 0.9730 and 0.7844, respectively. Therefore, the proposed deep learning method performs better to obtain the reflectivity with high accuracy in this case.

Conclusion

We propose a model-driven deep learning method to perform the nonstationary reflectivity inversion. Based on the nonstationary convolution model, the proposed method unrolls the iterative solutions derived by adopting the alternating iterative optimization algorithm into a deep neural network, in which we use the convolutional neural network to learn the gradient component. Then, we introduce a data-consistency loss function to implement the semi-supervised learning to make full use of the unlabeled data. Finally, we conduct a synthetic example to validate the proposed method, which

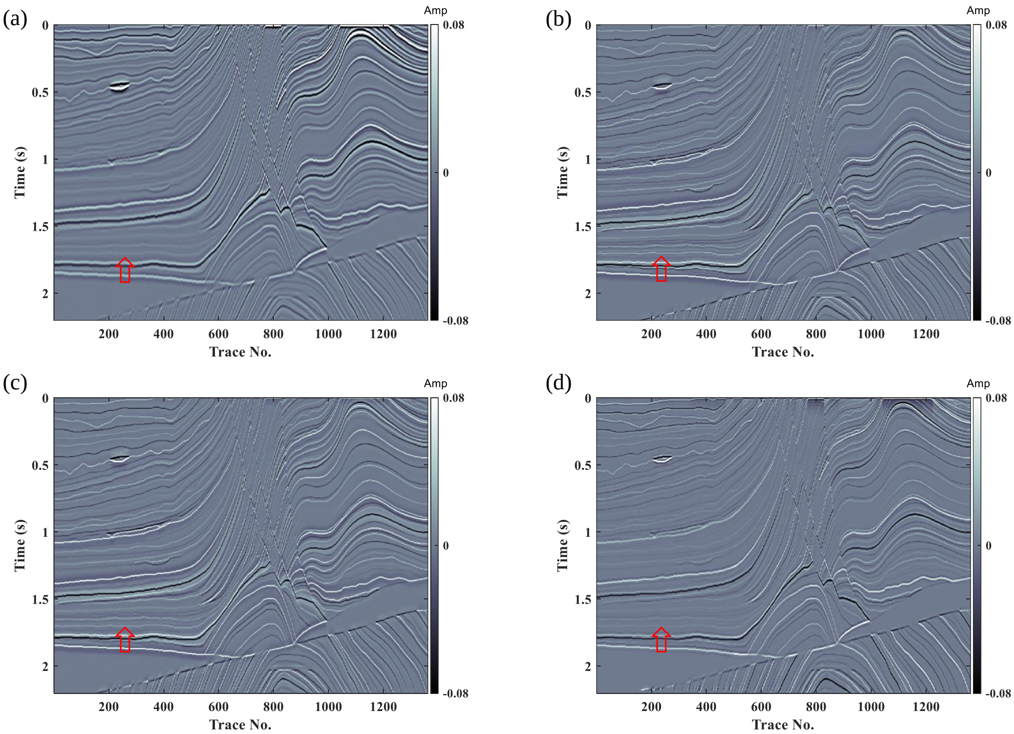

Figure 2: Estimated reflectivity coefficients from synthetic nonstationary data. (a) synthetic nonstationary data, (b) true reflectivity, (c) inverted reflectivity by using our proposed method, and (d) inverted reflectivity by using the non-learning deconvolution method.

performs better than non-learning nonstationary blind deconvolution.

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