Introduction

In seismic exploration, enhancing the vertical resolution of seismic data is an important issue because a higher resolution seismic data will definitely benefit the characterization of geological structure, lithological changes and fluid properties. Seismic reflectivity inversion (SRI) is such a technique that can enhance the vertical resolution of seismic data through an inversion procedure (Margrave et al., 2011; Cand`es and Granda, 2014; Haghshenas and Gholami, 2018). Usually, SRI methods are established based on the assumption that the seismic data satisfies the convolution model, which treats the seismic data as the convolution of seismic wavelet and the reflectivity. Based on this assumption, SRI enhances the resolution of seismic data by trying to compress the seismic wavelet in the data. However, it is well-known that the convolution model is unsatisfied because of the attenuation effect of earth. This effect leads to the fact that the energy of seismic data (especially for the high frequency components) will be attenuated along with the propagation path, thus, the seismic data will be nonstationary. As a result, properly handling the non-stationarity of seismic data is a prerequisite of the successful application of SRI. One effective way is to compensate the attenuation effect of seismic data before SRI (Wang et al., 2010). This way requires a reasonable Q factor model of the subsurface that is estimated from seismic data. However, the estimation of Q factor is known to be challenging. Another effective way is to separate the entire nonstationary seismic data into several stationary parts, perform stationary SRI for each part and derive a reflectivity model by combining the result of each part together (Wang et al., 2012). The key of this way is to set a reasonable criterion for data separation.

In this paper, we propose a new SRI method for enhancing the resolution of nonstationary seismic data. We firstly convert a nonstationary seismic data into a stationary one and then estimate the reflectivity based on it. Our key contribution is that we propose a new method for handling the non-stationarity of seismic data. Specifically, we propose a deep learning based data-driven method for data correction without the requirement of Q factor model or a carefully predefined criterion for the separation of the nonstationary data. In the proposed method, we separate the entire data into several parts based on the picked horizons, establish a nonlinear relation, which is based on the deep neural network, for each part, and convert the nonstationary data into a stationary one using the nonlinear relations. The deep neural network is trained based on the training dataset generated from the original nonstationary data and the well-log data. Numerical examples verify the effectiveness of the proposed method.

Seismic reflectivity inversion (SRI)

Seismic reflectivity inversion (SRI) is a technique that enhances the vertical resolution of seismic data by compressing seismic wavelet. SRI is often applied to post-stack seismic data. According to the convolution model, a single trace post-stack seismic data can be expressed as

\[
s = Wr = \begin{bmatrix} w_1 & w_2 & \cdots & w_L \\
  \vdots & w_2 & \cdots & \vdots \\
  w_L & \cdots & w_2 & \vdots \\
  \vdots & \vdots & \ddots & \vdots \\
  \vdots & \vdots & \vdots & w_L 
\end{bmatrix} \begin{bmatrix} r_1 \\
  r_2 \\
  \vdots \\
  r_{N_r} \end{bmatrix},
\]  

where \(s=[s_1, s_2, \ldots, s_N]^T\) is the seismic data; the vector \(w=[w_1, w_2, \ldots, w_L]^T\) denotes the wavelet with a length of \(L\). Based on the forward problem shown above, SRI can be formulated as an inverse problem to estimate reflectivity from seismic data as follows:

\[
\hat{r}^* = \arg\min_{\tilde{r}} ||s_{obs} - s_{pre}||_2^2 + \lambda ||\tilde{r}||_1,
\]

s.t. \(s_{pre} = W\tilde{r}\),

where \(\hat{r}^*\) is the optimal reflectivity, which corresponding to a best match of the observed seismic data \(s_{obs}\) and the predicted one \(s_{pre}\); \(||\tilde{r}||_1\) is the regularizer to constrain the reflectivity to be sparse; \(\lambda\) is the
regularization parameter to balance the two terms in the misfit function.

**Deep learning aided SRI (DLA-SRI) for nonstationary seismic data**

In this part, we will detailed introduce the proposed method. As introduced in equation 1, conventional SRI method is established on the convolution model but the fact is that seismic data is inevitably to be nonstationary because of the attenuation nature of earth and the convolution model is invalid in such cases. To deal with the nonstationary seismic data, we propose a new SRI method by modifying the original inverse problem, as shown in equation 2, to a new inverse problem as follows:

$$\hat{r}^* = \arg \min_{\hat{r}} \| g(s_{obs}) - s_{pre} \|_2^2 + \lambda \| \hat{r} \|_1,$$

where $g(\cdot)$ is a data correction operator that converts the original nonstationary seismic observed data into the corresponding stationary data. Given $g(\cdot)$, the inverse problem shown above can be effectively solved using the fast iterative shrinkage-thresholding algorithm (FISTA) (Beck and Teboulle, 2009).

![Figure 1](image1.png)

**Figure 1** The deep learning based data correction method: (a) the flowchart of the method and (b) the architecture of the deep neural network used in the method.

The key part of the proposed method is the establishment of the data correction operator $g(\cdot)$. Herein, we propose to establish $g(\cdot)$ using a deep learning based data-driven method. As shown in Figure 1 (a), the data correction operator is established through the following steps:

1) Picking the horizons of the subsurface based on the nonstationary seismic data.
2) Separating the entire seismic data into several parts based on the picked horizons.
3) For each part, training a deep neural network, whose architecture is shown in Figure 1 (b), to realize a nonlinear mapping from nonstationary data to stationary data.
4) Using the trained deep neural networks to correct the nonstationary data part by part.
5) Combining the corrected data of each part together to output the stationary data.

![Figure 2](image2.png)

**Figure 2** Illustration of how we generate several data pairs only using one single trace of data. The length of the whole trace is $N_t$ and we equally separate the whole trace into several subsections with a fixed length. The length of the subsection can be chosen as 1 or 2 times of the length of the wavelet.

Next, we will introduce how to generate the training dataset to guarantee the successful training of deep neural network. In the proposed method, we generate the training dataset for each part based on the nonstationary data and the stationary synthetic data generated based on the reflectivity from the well-log data. We separate each trace of both the nonstationary observed data and the stationary synthetic data
into several subsections instead of treating them as a whole, as shown in Figure 2. Benefiting from this separation scheme, the size of the training dataset can be sufficient large even though only a few wells are available in practice.

**Synthetic example**

In this part, we will use a synthetic example to verify the effectiveness of the proposed method. This example is based on a modified Marmousi model, which has 1201 traces and each trace has a length of 1.28 s. Figure 3 (a) and (b) show the true reflectivity model and the Q factor model of the modified Marmousi model, respectively. Three pseudo wells, which are located at traces 100, 800 and 1100, are used to generate the training datasets. The Ricker wavelet with the peak frequency of 30 Hz is used to generate data.

![Figure 3](image3.png)

**Figure 3** The modified Marmousi model: (a) the true reflectivity model and (b) the Q factor model.

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**Figure 3** The modified Marmousi model: (a) the true reflectivity model and (b) the Q factor model.

The seismic data: (a) the stationary data generated based on the true reflectivity model, (b) the nonstationary data generated based on the true reflectivity and the Q factor models, and (c) the corrected data generated from (b) using the proposed correction method. The PSNR of (b) and (c) are 23.2724 dB and 42.0541 dB, respectively.

![Figure 4](image4.png)

**Figure 4** The seismic data: (a) the stationary data generated based on the true reflectivity model, (b) the nonstationary data generated based on the true reflectivity and the Q factor models, and (c) the corrected data generated from (b) using the proposed correction method. The PSNR of (b) and (c) are 23.2724 dB and 42.0541 dB, respectively.

Figure 4 (a)-(c) show three different seismic data, which are the stationary data, the nonstationary data and the corrected data, respectively. Compared with the stationary data, the nonstationary one has weaker energy in the deep part because of the attenuation. After correction, the energy of the deep part is significantly enhanced and the corrected data appears to have a good consistency with the stationary data since its PSNR is 42.0541 dB. This is an evidence that the proposed deep learning based data correction method is effective in this example.

![Figure 5](image5.png)

**Figure 5** The estimated reflectivity models: (a) and (b) are estimated using conventional SRI based on the stationary seismic data and the nonstationary one, respectively, and (c) is estimated using the proposed method based on the nonstationary data. The PSNR of (a), (b) and (c) are 39.1183 dB, 30.1607 dB and 37.8477 dB, respectively.

Based on the three seismic data shown in Figure 4, we estimate the reflectivity models and the results are
shown in Figure 5. We can see that conventional SRI can not estimate a reasonable reflectivity model based on the nonstationary data since the PSNR is only 30.1607 dB. In contrary, reflectivity model estimated by the proposed method is significantly improved since its PSNR is 37.8477 dB. In addition, this model is comparable with the estimated model using conventional SRI based on the stationary data. These results verify the effectiveness of the proposed method and also clearly demonstrate its advantages over conventional method.

Field data example

The proposed method has also been applied in a field data example. The field post-stack seismic data has 1001 traces and each trace with a length of 1.1 s. We apply the proposed method in this example and the results are shown in Figure 6. It is clear from the results that the corrected seismic data has balance energy for both the shallow and the deep part, and the estimated reflectivity model appears to have a good consistency with the well-log data. This field data example further verifies the effectiveness of the proposed method.

Figure 6 The results of the proposed method in the field data example: (a) the corrected seismic data and (b) the estimated reflectivity model. The well located at trace 470 is shown for comparison.

Conclusions

In this paper, a deep learning aided seismic reflectivity inversion (DLA-SRI) method is proposed for nonstationary seismic data. DLA-SRI utilizes a deep learning based data correction operator to handle the non-stationarity of seismic data, and converts the nonstationary inverse problem into a stationary one. Using synthetic and field data examples, we verified the effectiveness of the proposed DLA-SRI method.

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References


