Seismic Simultaneous Source Separation via an unsupervised deep learning method

Introduction

In seismic exploration, simultaneous source acquisition technology has demonstrated that it can diminish acquisition cost using shorter survey time or improve the quality of seismic data by densely sampled or wide-azimuth sources (Berkhout, 2008). However, this type of acquisition will produce blended data corrupted by severe interference noise, which brings great challenges to the following steps of seismic data processing. Therefore, simultaneous source separation also known as deblending, which aims to separate the blended data into conventional data, is of great importance. There are two main kinds of simultaneous source separation methods: filtering and inversion methods. The filtering methods are based the assumption that the blending noise exhibits as incoherent noise in different domains rather than in common shot domain in the scenario of small random time-delay firing. Several classic methods can be used to suppress the blending noise, such as median filter (Huo et al., 2012) and convolutional neural network (CNN) (Sun et al., 2020; Zu et al., 2020). The inversion methods construct the separation of blended seismic data as an inverse problem and add regularization to obtain a stable solution (Mansour et al., 2012; Zhou et al., 2016).

Current CNN based deblending methods (Sun et al., 2020; Zu et al., 2020) are constructed as filtering form rather than inversion methods. And also the network training procedure usually requires for large amounts of prior training pairs, which is not always feasible for seismic data processing. Deep image prior (DIP) (Ulyanov et al., 2018) has been applied in seismic data processing such as random noise suppression (Liu et al., 2020) and data interpolation (Kong et al., 2020). Inspired by the DIP framework, in this abstract, we present an unsupervised deep learning based method to separate simultaneous source data where no prior training pairs are needed. Specifically, we construct the corresponding inverse problem and use the DIP as the implicit regularization to capture useful information of unblended data. Synthetic and field data examples are tested to prove the effectiveness of the presented method.

Method

A. Problem construction

In the framework of simultaneous source acquisition (Berkhout, 2008), multiple sources are fired in a sequential order with regular time interval added by a certain random time delay, which results that the individual source data are blended and further received by the same receiver arrays. Particularly, for one fixed receiver, the blended seismic data can be written as

\[ \mathbf{b} = \mathbf{\Gamma d}, \]

where \( \mathbf{d} \in \mathbb{R}^{(m \times n) \times 1} \) is vector form of the conventional common receiver gather (CRG) with \( n \) shots and \( m \) time samples. \( \mathbf{\Gamma} \in \mathbb{R}^{k \times (m \times n)} \) denotes the blending matrix which is constructed by \( n \) identity matrices of size \( m \times m \) that are arranged in an overlapping block diagonal structure (Zhou et al., 2016). Because of the blending effect, the measurement \( \mathbf{b} \in \mathbb{R}^{1 \times 1} \) is a single long vector of length \( k \) (\( k \ll m \times n \)), which indicates the overlapped superposition of sequential traces of conventional CRG data. Generally, the survey time ratio (STR) can be used to estimate the economic performance of the simultaneous source acquisition, which is commonly defined as (Mansour et al., 2012)

\[ \text{STR} = \frac{\text{time of conventional shooting of } n \text{ traces}}{\text{time of blending shooting of } n \text{ traces}}. \]

According to Equation (2), the subsampling ratio \( \gamma = 1/\text{STR} \) can be approximated by \( k / mn \).

The goal of deblending is to recover the conventional seismic data \( \mathbf{d} \) from the blending measurement \( \mathbf{b} \), which can be constructed as an inverse problem. This problem is generally ill-posed, and thus a proper prior is considered to robustly solve it. The corresponding cost function can be constructed as

\[ \hat{\mathbf{d}} = \arg \min \| \mathbf{b} - \mathbf{\Gamma d} \|_2^2 + R(\mathbf{d}), \]

where \( \| \mathbf{b} - \mathbf{\Gamma d} \|_2^2 \) is the data fidelity term and \( R(\mathbf{d}) \) denotes the regularization term which describes the useful prior information of the convention seismic data \( \mathbf{d} \). Currently, some hand crafted priors have
been used for deblending, such as the sparsity (Zhou et al., 2016) and low-rankness (Cheng et al., 2015). However, the extreme complexity of seismic data will make it very difficult to obtain promising deblending results by using these hand crafted priors.

**B. Seismic simultaneous source separation via DIP regularized framework**

To capture more useful prior information from the blended data, we make use of the DIP regularized framework and assume that the conventional unblended seismic data \( d \) can be represented by an untrained deep generative network \( G(w; z) \). Here, the fixed random noise \( z \) is the input of network and \( w \) is the weight. Therefore, using the structure of the generator network \( G(w; z) \) as the implicit regularization, we can estimate the weight \( w \) rather than directly recovering \( d \) by the optimization in Equation (3). The corresponding cost function can be written as

\[
\bar{w} = \arg \min_w \| b - \Gamma G(w; z) \|^2.
\]

In order to solve the problem in Equation (4), we use an encoder-decoder architecture with skip connections as that of network \( G(w; z) \) (Ulyanov et al., 2018). The weight \( \bar{w} \) is randomly initialized and iteratively optimized using Adam optimizer. After a certain number of iteration, we can obtain the target unblended seismic data, which is the output of the network \( \tilde{d} = G(\bar{w}; z) \). An overview of our method is depicted in Figure 1.

![Figure 1](image)

**Figure 1** Overview of our proposed method.

**Examples**

We use the synthetic data from a portion of Marmousi model and a field data to test the effectiveness of our presented method. The recovery performance can be evaluated quantitatively by the following signal-to-noise ratio (SNR)

\[
\text{SNR}(d, \tilde{d}) = \log_{10} \frac{\| d \|^2}{\| \tilde{d} - d \|^2},
\]

where \( \tilde{d} \) is the recovery, and \( d \) is the conventional unblended data.

The first example is for synthetic data. Figure 2(a) shows one section of the unblended seismic data in the common receiver gather. This section contains \( n = 256 \) shots and \( m = 1024 \) time samples with 8m spatial intervals and 2ms temporal interval. In order to simulate the blending seismic data under sequential random time-dithering firing scheme, we set the subsampling ratio as \( \gamma = 1/\text{STR} = 0.25 \) and the random time dithering as \([-0.05s, 0.05s]\) shown in Figure 2(b). With the known blending matrix \( \Gamma \) and blended records \( b \), our presented method is used to recover the unblended conventional seismic data in the common receiver domain. The pseudo-deblending measurement with \( \text{SNR} = -4.77\text{dB} \) is shown...
Figure 2 Synthetic data example. (a) Original unblended seismic data. (b) The random time dithering sequence. (c) The pseudo-deblending measurement data. (d) The deblended result using our method. (e) The corresponding residual.

Figure 3 Field data example. (a) Original unblended seismic data. (b) The random time dithering sequence. (c) The pseudo-deblending measurement data. (d) The deblended result using our method. (e) The corresponding residual.
in Figure 2(c), and we can find that there is a lot of incoherent interference. Figure 2(d) and 2(e) show the deblending result with SNR = 15.26dB using our method and the corresponding residual, respectively. It can be seen that our method recovered the useful seismic data effectively and the corresponding residual is small enough to be negligible.

The second example is based on the numerical blending of field unblended seismic data. One of the sections shown in Figure 3(a) contains \( n = 128 \) shots and \( m = 512 \) time samples per trace. The spatial interval is 25m and the temporal sampling interval is 4ms. We set the subsampling ratio as \( \gamma = 1 / \text{STR} \approx 0.5 \) and the random time dithering as \([-0.05s, 0.05s]\) shown in Figure 3(b). The pseudo-deblending measurement with SNR = 0.05dB is shown in Figure 3(c), which contains severe incoherent noise. Figure 3(d) displays the corresponding recovery result with SNR = 7.39dB using our method, which is comparable to the clean unblended data shown in Figure 3(a). Figure 3(e) shows the corresponding error section that has little residual error.

Conclusions and Discussions

In the framework of seismic simultaneous source acquisition with random time dithering scheme, we construct the separation of the blended seismic data as an inverse problem, and present an unsupervised deep learning method which can avoid the problems of building large training data sets and generalization. Particularly, the Deep Image Prior (DIP) is introduced as the implicit regularization to iteratively capture useful coherent information from blended data, which finally generates the conventional unblended seismic data. The performance on the synthetic and field examples demonstrate that our presented method can recover the unblended seismic data effectively from the blended measurement data. Our future work will focus on improving recovery accuracy by modifying network topological structure and compare the presented scheme with the traditional ones.

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References