Introduction

Simultaneous sources acquisition, i.e. blended acquisition, is an important seismic data acquisition method to improve the efficiency or the data density. It allows multiple sources to be excited simultaneously in a short time interval, with each receiver receiving this information. The advantages of blended acquisition are to reduce acquisition time when obtaining the same amount of data, or improve the data density when the acquisition time is similar. In recent years, it becomes more and more important. However, the collected seismic data by using blended acquisition contains information of multiple sources, which poses challenges towards traditional seismic data processing, which requires separated data. Thus, deblending becomes necessary to provide separated gathers. Various methods have been developed for deblending, which can be mainly divided into filtering-based methods and inversion-based methods. By using a blending operator, being composed of a random time delay series, the blended data can be simulated and the blending noise shows randomness in some sorted domains, such as the common receiver domain, the common midpoint domain, or the common offset domain. Thus, Huo et al. (2009) proposed the multidirectional vector-median filter for deblending which extended the traditional median filtering from a scalar version to the vector version. For inversion based deblending methods, Wang and Geng (2019) proposed to implement the curvelet transform on the principal frequency wavenumber (PFK) domain data instead of the time space (TX) domain data to improve the deblending efficiency as well as guarantee the accuracy.

For the traditional deblending methods, optimal parameters need to be selected by trial and error to achieve satisfactory results for different seismic data, which takes lots of time, especially for large volume seismic data. With the advancement of the computer technology, especially the development and application of GPU, deep learning plays an important role in different fields, such as interpolation, denoising, fault detection etc. Here, intelligent deblending is researched in this abstract based on U-net. Previously, Richardson and Feller (2019) used a U-net model incorporating a ResNet architecture for denoising and deblending on synthetic seismic data. Zu et al. (2019) proposed an iterative deblending for simultaneous source data using deep neural network. However, most of these methods require a large amount of labeled data for network training to achieve satisfactory deblending results. While field data lacks the labeled data, which limits its wide application. Thus, we designed a U-net for intelligent deblending, combined with the traditional iterative threshold shrinkage algorithm. A set of synthetic data with labels are used for U-net training and validation, and then the trained U-net is transferred and finetuned by using parts of field data with labels. Finally, the finetuned U-net is used for intelligent deblending of the left field data. The deblending performance is promising compared with the curvelet transform based thresholding method, which demonstrates the validity of the proposed intelligent deblending algorithm in accuracy, stability and efficiency.

Method

Compared with the fully connected layers, the parameters in CNN based U-net are much reduced which can be beneficial for the network updating with high efficiency. U-net was first proposed by Ronneberger et al. (2015), which was mainly used in segmentation of large-scale medical image. It includes two parts, encoding (i.e. feature extraction or downsampling) and decoding (i.e. information recovery or upsampling), like a U-shape. During the decoding procedure, channel connection technology is used to accelerate the training efficiency and guarantee the recovery accuracy. That’s why we choose U-net for intelligent deblending in this abstract and the designed structure is shown in figure 1. The left part denotes the encoding procedure to extract the features hidden in seismic data, and the input is blended seismic data. The right part represents the decoding procedure to approach the labelled data. In the designed U-net, there exits convolution layer, max pooling layer, nonlinear RELU operator etc, to characterize seismic data nonlinearly through self-learning.

In figure 1, orange arrows represent max pooling layers with a size 2 by 2 during the encoding procedure, which can extract the hidden features of seismic data. The red arrows represent deconvolution layers through an upsampling operator with a step size 2, followed by RELU, during the decoding process. The blue arrows represent the convolution layers followed by a nonlinear RELU operator, and the size of the convolution kernel is 3 by 3. The black arrows represent the convolution
layer without RELU operator to approach the labelled data. The green arrows represent the channel connection to accelerate the network training and guarantee the recovery precision.

Figure 1 The designed U-net for intelligent deblending.

When the U-net is established, a set of synthetic data with labels are used to train and valid the U-net. Firstly, 80 percent synthetic data is used for U-net training and we can obtain the training U-net $\theta^*$.

And then, the left 20 percent synthetic data is used for U-net validation. Finally, 20 percent field data are used to finetune the trained U-net $\theta^*$ to obtained the finetuned network $\tilde{\theta}^*$ based on transfer learning strategy, during which the labels of the used field data can be obtained by using the traditional curvelet transform based iterative thresholding method. The finetuned network $\tilde{\theta}^*$ is used to deblend the left 80 percent field data. To improve the deblending accuracy, the iterative thresholding shrinkage algorithm is incorporated for 2-3 iterations to obtain separated seismic data accurately which can be beneficial for subsequent seismic data processing. Seismic data blended acquisition in the time domain can be characterized in equation (1a), and pseudo-deblended data can be expressed in equation (1b),

\[
\begin{align*}
\mathbf{d}_1 &= \mathbf{d}_1 + \Gamma_2 \mathbf{d}_2 = \Gamma \mathbf{d} \\
\Gamma^* \mathbf{d}_1 &= \mathbf{d} + (\Gamma^* \Gamma - I) \mathbf{d}
\end{align*}
\]

(1a)  
(1b)

$d_1$ is the first source data, $\Gamma_2$ is blending operator towards the second source $d_2$, $d_{bl}$ is the blended data. $\Gamma$, $\mathbf{d}$ are the blending operator and unblended seismic data. $\Gamma^*$ is the conjugate operator of the blending operator and $I$ is the identity matrix. For intelligent deblending, the U-net can be used to approach seismic, and the mathematical formula can be expressed as,

\[
\phi(\mathbf{t}) = \frac{1}{2} \| f(\Gamma^* \mathbf{d}_{bl}; \mathbf{t}) - \mathbf{d} \|^2.
\]

(2)

Synthetic data are used to train and valid the U-net, and 20 percent field data with labels to finetune the trained U-net. The finetuned U-net $\tilde{\theta}^*$ is used for intelligent deblending for field data, as shown in equation (3),

\[
\mathbf{d}_{act} = f(\Gamma^* \mathbf{d}_{act}; \tilde{\theta}^*).
\]

(3)

In order to improve the performance of intelligent deblending, the iterative algorithm is incorporated, as expressed as in equation (4),

\[
\mathbf{d}_{act,i+1} = f(\Gamma^* \mathbf{d}_{act,i} - (\Gamma^* \Gamma - I) \mathbf{d}_{act,i}; \tilde{\theta}^*). 
\]

(4)

where $d_{act,i}$ denotes the iterative deblending estimation in the $i$th iteration. After 2-3 iterations, we can get high-quality deblending results, i.e. separated wavefield, which can improve the accuracy of subsequent seismic data migration and inversion.

Examples
To demonstrate the validity of the proposed intelligent deblending algorithm. A set of numerical examples are carried out. Firstly, 256 shot gathers are generated which are used to train (80 percent as training data) and valid (20 percent as validation data) the U-net. Secondly, for field data with 128 shots, 20 percent (25 pairs) are used to finetune the trained U-net, during which the labels of field data can be obtained by using traditional sparse transform based the iterative thresholding algorithm. The finetuned U-net combined with the iterative strategy, as shown in equation (4), can be used to deblend the left 103 blended field gathers. In order to assess the deblending performance of the proposed method, the recovered signal to noise ratio (SNR) is calculated. 20 of them are shown in figure 2, as shown by red stars. For a better comparison, the traditional curvelet transform based iterative threshold shrinkage algorithm is used for deblending, and the recovered SNRs are denoted by black circles. Figure 2 shows that the proposed method can achieve a better deblending result more stably. Besides, the proposed method is more efficient, as the main consumed time lies in the training procedure. After training, the intelligent deblending is relatively efficient.

For qualitative comparisons, the 5th common receiver gather in figure 2 is extracted for comparisons, as shown in figure 3. Figure 3(a) represents the blended seismic data in the common receiver domain, in which the signal is coherent and the blending noise shows randomness. Figure 3(b) shows the deblending results by using the curvelet transform based iterative thresholding shrinkage algorithm, we can see that it can obtain the separated gather reasonably while it takes a large computational burden. By using the proposed method, we can obtain the deblending results efficiently, as shown in figure 3(c). The recovered SNRs are 18.07 dB and 17.36 dB, respectively, which are almost consistent with each other.

Figure 2 The recovered SNRs by using the proposed method as marked by red stars and the traditional curvelet transform based iterative thresholding shrinkage algorithm as marked by circles.

Figure 3 The deblending results for the 5th receiver in figure 2. (a) represents the blended data, (b) represents the deblended result by the traditional deblending method, and (c) represents the deblending data by the proposed method.

To further illustrate the performance of the proposed method, the 10th receiver in figure 2 is also shown in figure 4. Figures 4(a, b, c) represent the blended seismic data, deblending data by the traditional method, and the proposed method, respectively. Figure 4(b) shows that there exists much
blending noise left, and the proposed method can remove the blending noise properly, as shown in figure 4(c). The recovered SNRs are 6.43 dB and 14.15 dB, respectively, which demonstrates the superiority of the proposed method. Figures 2, 3 and 4 demonstrate the validity of the proposed method in deblending accuracy and stability. Besides, the proposed intelligent method is also of high efficiency to obtain separated gathers.

![Figure 4](image_url)

**Figure 4** The deblending results for the 10th receiver in figure 2. (a) represents the blended data, (b) represents the deblended result by the traditional deblending method, and (c) represents the deblending data by the proposed method.

**Conclusions**

We propose an intelligent seismic data deblending method based on deep learning based U-net. By using a set of synthetic data for U-net training and validation, and then parts of field data with labels are used to finetune the trained U-net. The finetuned U-net incorporated with the iterative strategy are used to deblend the left field data. The deblending performance is promising to obtain separated gathers. For further comparisons, traditional sparse curvelet transform based iterative threshold shrinkage algorithm is carried out for deblending. The comparisons show that the proposed intelligent method can provide separated gathers accurately and stably. Besides, the proposed method is also of high efficiency because the main computational burden lies in training procedure and the deblending procedure is relatively efficient. The deblending gathers can be beneficial towards the following traditional seismic data migration or inversion.

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**Reference**


