

Original Paper

Accurate reconstruction method of virtual shot records in passive source time-lapse monitoring based on SBA network

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ABSTRACT

Passive source imaging can reconstruct body wave reflections similar to those of active sources through seismic interferometry (SI). It has become a low-cost, environmentally friendly alternative to active source seismic, showing great potential. However, this method faces many challenges in practical applications, including uneven distribution of underground sources and complex survey environments. These situations seriously affect the reconstruction quality of virtual shot records, resulting in unguaranteed imaging results and greatly limiting passive source seismic exploration applications. In addition, the quality of the reconstructed records is directly related to the time length of the noise records, but in practice it is often difficult to obtain long-term, high-quality noise segments containing body wave events. To solve the above problems, we propose a deep learning method for reconstructing passive source virtual shot records and apply it to passive source time-lapse monitoring. This method combines the UNet network and the BiLSTM (Bidirectional Long Short-Term Memory) network for extracting spatial features and temporal features respectively. It introduces the spatial attention mechanism to establish a hybrid SUNet-BiLSTM-Attention (SBA) network for supervised training. Through pre-training and fine-tuning training, the network can accurately reconstruct passive source virtual shot records directly from short-time noisy segments containing body wave events. The experimental results of theoretical data show that the virtual shot records reconstructed by the network have high resolution and signal to noise ratio (SNR), providing high-quality data for subsequent monitoring and imaging. Finally, to further validate the effectiveness of proposed method, we applied it to field data collected from gas storage in northwest China. The reconstruction results of field data effectively improve the quality of virtual records and obtain more reliable time-lapse imaging monitoring results, which have significant practical value.

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1. Introduction

In recent decades, time-lapse seismic has become the most effective geophysical method for monitoring subsurface changes during oil field development (Fanchi et al., 1999; Cotton et al.,

2018; Wang et al., 2021), with high accuracy. Wang et al. (1998) used time-lapse seismic technology for the first time to predict the distribution of remaining reservoirs after carbon dioxide flooding. Wulff and Svein (2002) conducted indoor experiments and used time-lapse seismic response to monitor fluid movement and saturation changes, confirming that time-lapse seismic response can effectively monitor fluid migration. With the growing global focus on carbon neutrality and carbon peaking, some scholars have used time-lapse seismic monitoring technology to observe the

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changes in underground formations after the injection of CO₂, and monitored the diffusion path of CO₂ injected into deep underground reservoirs, confirming the time-lapse seismic method is the most effective method to monitor the safety of CO₂ geological storage (Ivanova et al., 2012; White, 2013; Ivandic et al., 2018). However, due to issues such as the high cost of data acquisition, inconsistency in acquisition, severe environmental impact, and long acquisition cycle, continuous long-term monitoring using time-lapse seismic method is often impossible.

With the widespread application of node instruments in oil and gas exploration (Zhao et al., 2015; Lei et al., 2018), it has become possible to continuously collect background noise through passive source seismic methods for long-term continuous monitoring. Since the last century, the passive source seismic interferometry (SI) method (Wapenaar et al., 2008; Draganov et al., 2009) has gradually become an alternative to active source exploration due to its low cost, non-destructive, and no acquisition restrictions. The core of this method is to extract active source-like surface waves and body waves (Green's function) from background noise through interferometry for subsequent imaging. It has achieved great success in natural earthquakes and near-surface exploration, and is widely used to construct high-resolution shear wave velocity structures (Nakata et al., 2011; Cheng et al., 2016; Lu et al., 2018; Mordret et al., 2020; Wu et al., 2023) and underground monitoring (Mao et al., 2022). In passive source body wave exploration, development is relatively slow due to the quality of collected data. Compared with surface waves, body waves have higher frequency and detection depth, can be applied to more scenarios, and have attracted much attention. Several studies have shown that passive SI body wave imaging has important potential in underground monitoring. Cheraghi et al. (2015) successfully located the mineral source using passive seismic interferometry and applied it to the four-dimensional dynamic monitoring of CO₂ storage. Boullenger et al. (2015) used ambient noise seismic interferometry (ANSI) to invert the time-lapse reflection response of the Ketzin carbon storage reservoir in Germany and verified the feasibility of ANSI in CO₂ storage projects. Cheraghi et al., (2017) analyzed the results of passive seismic interferometry of CO₂ reservoir data in Saskatchewan, Canada, and tested the method's imaging ability and time-lapse imaging potential of underground geological structures. Gu et al. (2021) used dense arrays to record background noise in coal mining and mapped passive seismic structural images of coal mines. Wu et al., (2025) proposed a passive source time-lapse seismic method, which was successfully applied to the monitoring of waterflooding in oilfield sites. However, affected by the complex acquisition environment and ubiquitous noise sources near the surface, most of the effective body wave reflection from the underground are submerged by other noise, resulting in virtual shot records SNR and resolution are reduced, which challenges to subsequent monitoring interpretation. To extract body waves that are beneficial to seismic background noise imaging, many scholars have conducted extensive research (Corciulo et al., 2012; Vidal et al., 2014; Hartstra et al., 2017; Chamarczuk et al., 2019; Fang et al., 2022). Nevertheless, to recover more reliable and robust virtual shot records, passive source SI must satisfy the assumptions of the randomness of underground seismic sources and valid body wave records for a long enough time. However, in actual seismic data sets, these assumptions often do not hold true at the same time, which is also the direct reason why existing methods can not reconstruct high-quality virtual shot records. Therefore, how to overcome the limitations of the assumption and reconstruct more reliable virtual shot acquisition records deserves further study.

Because deep learning models can solve complex nonlinear problems, they have seen widespread application in seismic data

processing in recent years. These applications include seismic data denoising (Liu et al., 2022, 2023), full waveform inversion (Zhang and Gao, 2021), seismic positioning (Saad and Chen, 2020; Vinard et al., 2022), data reconstruction (Pan et al., 2020; Wang et al., 2024), first-break picking (Wu et al., 2024), reservoir parameter inversion (Liu et al., 2024), with satisfactory results. Deep learning methods are also used in passive source seismic exploration, including extracting surface wave signals from natural earthquakes or near-surface noise, retrieving body wave events, etc. (Zhang et al., 2020; Mezyk et al., 2021; Chen et al., 2023). These successful cases bring hope for accurately reconstructing passive source virtual shot records from short-term noise segments containing body wave signals. In terms of reconstructing virtual shot records, Sun and Demanet (2022) used a deep learning network to recover high-precision virtual shot records from background noise records for the first time, overcoming the time and space limitations, but still required sufficiently long records containing body waves. Ma et al. (2024) proposed a passive source SI method combined with deep transfer learning, which can extract real-time empirical Green's functions from a small amount of noisy data. Zhao et al. (2024) designed a special network to eliminate coherent noise and false events in virtual shot records and improve the quality of virtual shot records. The above studies have achieved good theoretical data results. So far, there is almost no research on using deep learning to reconstruct virtual shot records from the field passive source data. To fill this gap, this paper innovatively proposes a virtual shot reconstruction method based on SBA network, and attempts to use the known first active source data as a prior for secondary training. This method breaks through the assumptions of traditional SI, and proposes a network framework that combines UNet (Ronneberger et al., 2015), BiLSTM (Siami-Namini et al., 2019) and attention mechanism (Vaswani et al., 2017), which can more effectively extract temporal and spatial features, accurately reconstruct passive source virtual seismic records from short-term noise segments containing body wave signals. The method first retrieves body wave events from massive noise data and constructs virtual shot records containing effective body wave signals as input data. Next, the network model is trained. Finally, theoretical data and actual field data that have not participated in training are tested. The test results show that the reconstruction results effectively improve the quality of the virtual shot records, obtain more reliable time-lapse imaging monitoring results, and verify the effectiveness and superiority of the proposed method.

The remainder of this paper is organized as follows: Section 2 introduces the relevant theories based on seismic interferometry and the network structure for virtual shot collection reconstruction, and discusses in detail how to create training dataset. Section 3 gives the application of theoretical data (in line with the actual acquisition environment) and actual data, proving that this method can improve the quality of reconstructed virtual shot collections. Finally, we draw conclusions in Section 4.

2. Theory and methods

2.1. Basis principle of seismic interferometry (SI)

SI is the basis of passive source seismic imaging. It mainly uses interference technology to extract Green's function from the background noise collected by the receiver, which can reconstruct seismic a response similar to that of an active source, thereby generating a virtual seismic source. After years of development, SI currently has methods such as cross-correlation, deconvolution, and cross-coherence method. Among them, cross-correlation SI is widely used in the processing of passive source seismic data due to

its high efficiency and stability. According to the correlation reciprocity theorem, we can derive formulas suitable for passive source cross-correlation SI. Assume that the earthquake source is located underground, let A and B be the two receivers on the surface, and the received seismic records are $S(x_A, t)$ and $S(x_B, t)$ respectively, then the reconstructed time domain reflection response (Green's function) is (Wapenaar and Fokkema, 2006):

$$R(x_A, x_B, t) + R(x_A, x_B, -t) = \delta(x_{H,B} - x_{H,A})\delta(t) - S(x_A, t) \otimes S(x_B, -t) \quad (1)$$

where $R(x_A, x_B, t)$ represents the seismic reflection record excited by receiving point x_B and received by receiving point x_A , also known as the causal part; $R(x_A, x_B, -t)$ represents non-causal part; δ represents the Dirac function; $x_{H,A}$ and $x_{H,B}$ are the horizontal components at x_A and x_B ; $S(x_A, t)$ and $S(x_B, t)$ represent the

transmitted responses received by the two surface receivers at x_A and x_B respectively, and $\otimes$ represents the convolution operation. The schematic diagram of Eq. (1) is shown in Fig. 1, and for more detailed formula derivation, see Wapenaar and Fokkema, 2006.

It is worth noting that since the reconstruction result of Eq. (1) is affected by the source wavelet, this paper performs amplitude normalization and spectrum whitening on the original records, and then normalizes the reconstruction results. Among the basic assumptions of SI, the derivation of the above formula requires that the medium is lossless, the wave field is equally divided, and the underground seismic sources are evenly distributed. However, in most cases, it is difficult to meet all of the above conditions. Without knowing the true distribution of underground sources, we usually use the cross-correlation stack method to process long-term background noise data to reconstruct a virtual shot records with arbitrary surface geophone positions as shot points. However,

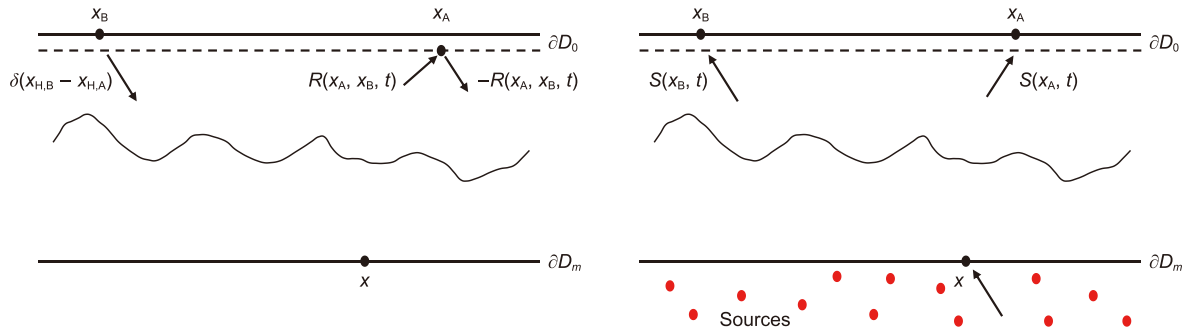


Fig. 1. Schematic diagram of the reflected wavefield excited at point B and received at point A (left). Schematic diagram of the transmitted wavefield excited at point x (right).

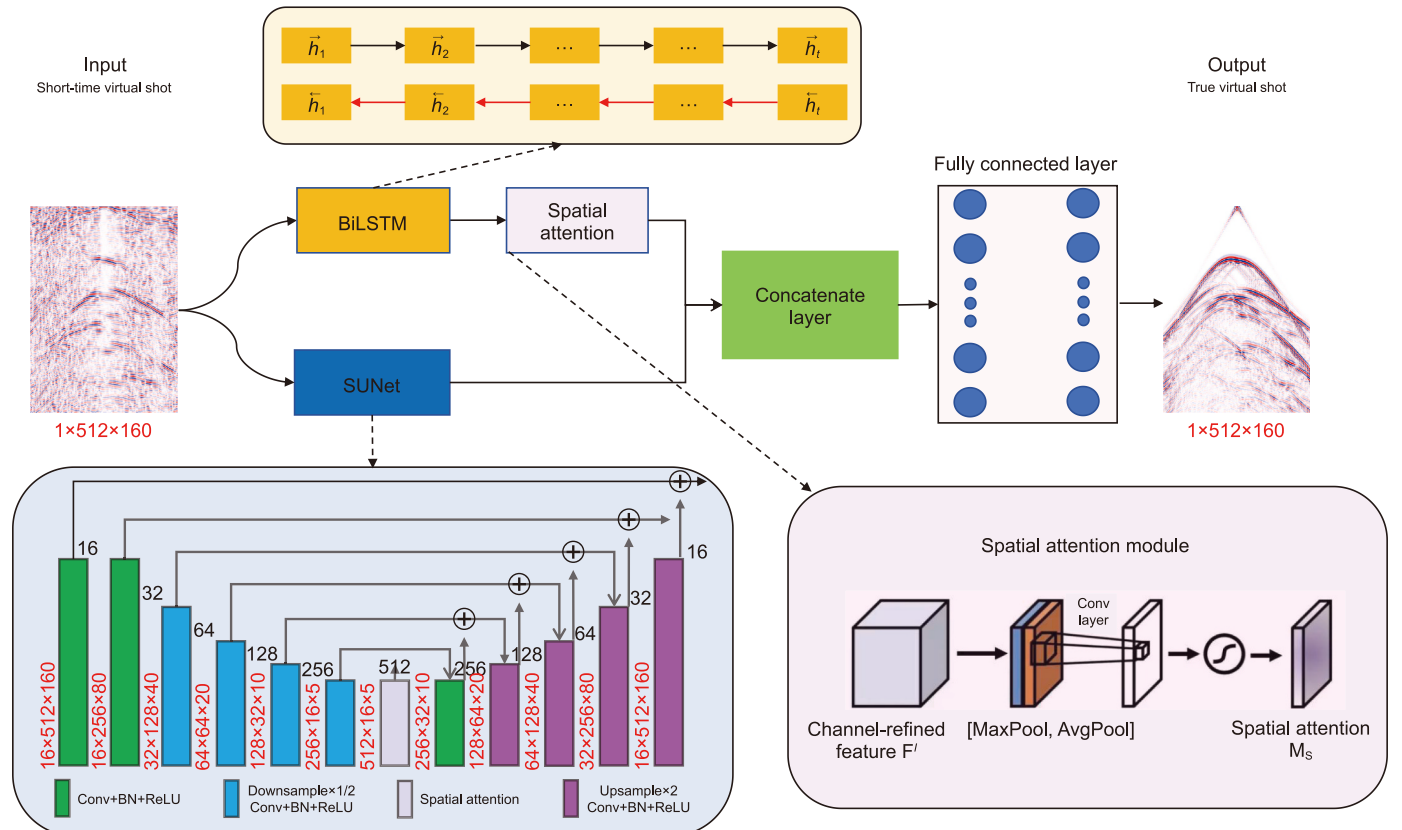


Fig. 2. The network architecture of hybrid SUNet-BiLSTM-Attention (the red characters represent dimensional changes, with the first dimension being channel changes).

Table 1
List of hyper-parameters.

Stage	Hyper-parameters	Selected
Training	Optimizer	Adam
	Pre-training batch size	16
	Fine-tuning batch size	4
	Learning rate	0.002
	Loss function	MAE
	Epochs	200
	Dropout	0.2
	Activation function	ReLU
	Training sample size	512×160
	GPU	$4 \times 1080Ti$

it is often challenging to obtain high-resolution virtual shot records like active source records. In addition, in filed data, due to the existence of a large amount of noise data, there are fewer effective body wave signals, and the SNR and resolution of the reconstructed virtual shot records are further reduced (Liu et al., 2021). Therefore, accurate reconstruction of virtual shot records faces the problem of spatial limitations of source distribution and time limitations of effective records of background noise (Thorbecke and Draganov, 2011).

2.2. SBA network structure for reconstruction

Deep learning has the ability to solve complex nonlinear problems. Based on the existing problems in reconstructing virtual shot records, we build an end-to-end supervised learning network to solve them. We design a hybrid SUNet-BiLSTM-Attention (SBA) network which can better extract spatial and temporal features from the training data to find the mapping between the virtual shot records constructed from short-time noisy segments containing body waves to the real virtual shot records. This particular architecture is chosen due to the following factors. First, the UNet network can effectively extract spatial features (Ronneberge et al., 2015). Then, the BiLSTM network excels at extracting temporal features, allowing for a more comprehensive understanding of the input data (Siarni-Namini et al., 2019). Finally, the attention mechanism is used to redistribute weights to extract spatiotemporal features and integrate them into more salient features. The network architecture of hybrid SUNet-BiLSTM-Attention is shown in Fig. 2. It consists of 4 main parts: a spatial attention UNet network (SUNet), a BiLSTM network, an attention mechanism, and a fully connected layer. The idea of this model is to send the virtual shot records after the cross-correlation stack of short-term noise segments containing body waves into channel 1 and channel 2.

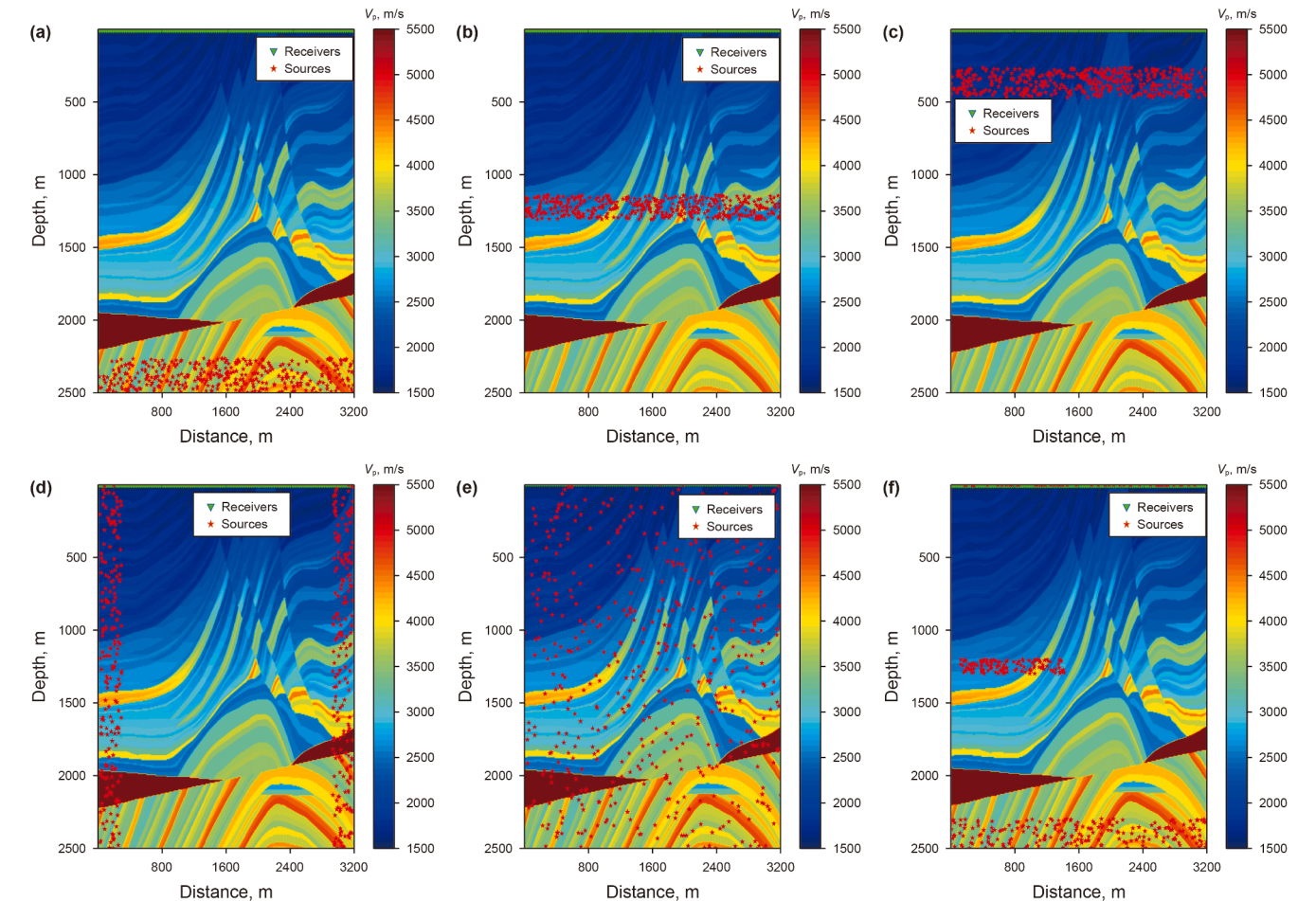


Fig. 3. Different seismic source distribution models: (a) deep sources, (b) middle sources, (c) shallow sources, (d) two-side sources, (e) full-space random sources, (f) actual acquisition situation sources.

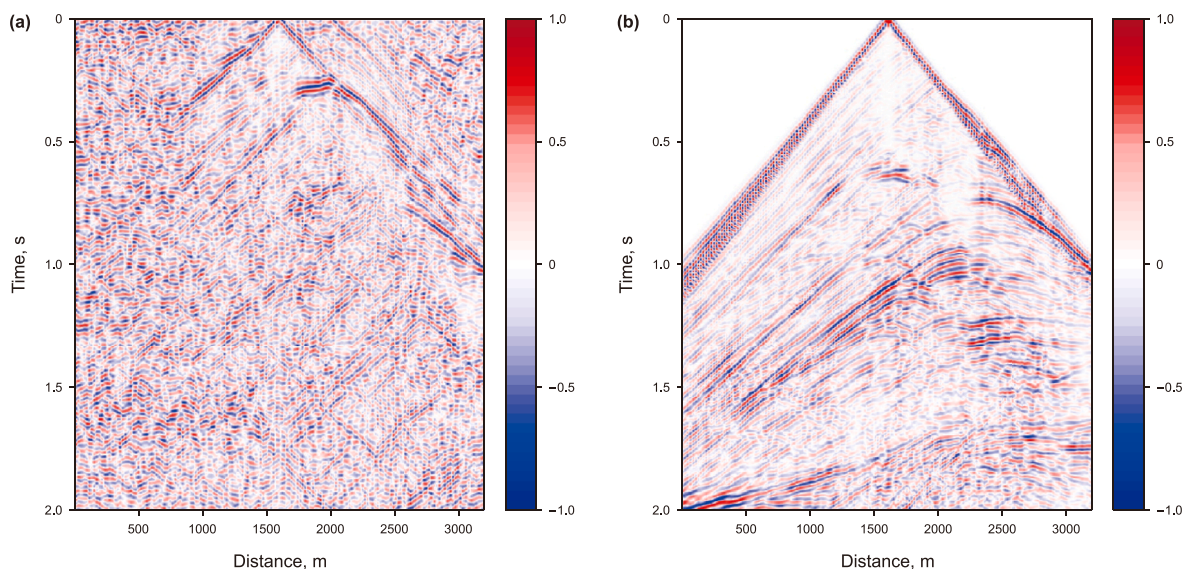


Fig. 4. (a) Reconstructed virtual shot records from 2-min long data by traditional cross-correlation SI method (input). (b) Active source records corresponding to the shot point position using traditional cross-correlation SI method (output).

Channel 1 uses the SUNet network to extract nonlinear spatial features, and channel 2 uses the BiLSTM network to learn temporal correlation between input data. The features extracted by the two channels are then fused, and a fully connected layer is applied for

the final output to reconstruct the real virtual shot records. The training hyperparameters of the network are shown in Table 1. It is worth noting that, unlike the training method of other papers, the input data is not divided into regular sizes similar to 128×128 . In

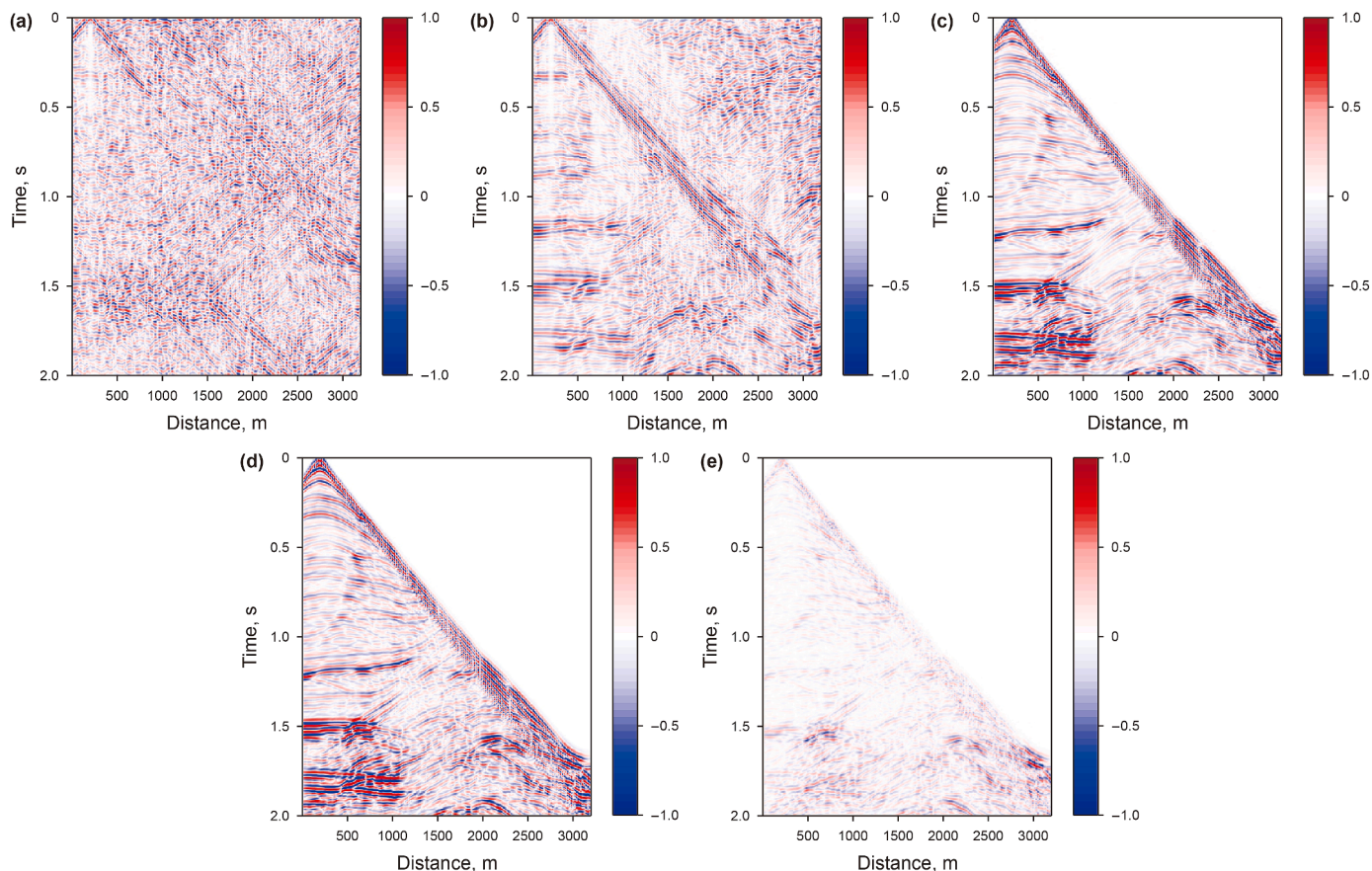


Fig. 5. (a) Reconstructed virtual shot records from 2-min long data by traditional cross-correlation SI method. (b) Reconstructed virtual shot records from long-term data by traditional cross-correlation SI method. (c) Reconstructed virtual shot records by SBA Network. (d) Real virtual shot records (active source records). (e) Residual between (c) and (d).

Table 2
Comparison of ablation experiments in test sets.

Network model	Time consumption (training + testing)	AMSE	PCC
SBA	697 min	0.00016	90.05%
SBA (no attention)	594 min	0.00134	84.79%
Single BiLSTM	476 min	0.00405	72.38%
Single UNet	511 min	0.00296	76.65%

order to extract features to a greater extent without losing spatial information, we don't truncate the virtual shot records on the seismic trace (distance dimension), and the input data is each complete virtual shot records. The convolution kernel in the SUNet

network is 3×3 , and loss function of the SBA network is defined as:

$$\begin{cases} P_1 = f(x; \theta_1) \\ P_2 = f(x; \theta_2) \\ P_3 = f(x; \theta_3) \end{cases}$$
$$\text{MAELoss}(P, y) = \frac{1}{n} \sum_{i=1}^n |P_i - y_i|$$
$$\text{Loss} = \text{MAELoss}(P_1, y) + \text{MAELoss}(P_2, y) + \text{MAELoss}(P_3, y)$$

(2)

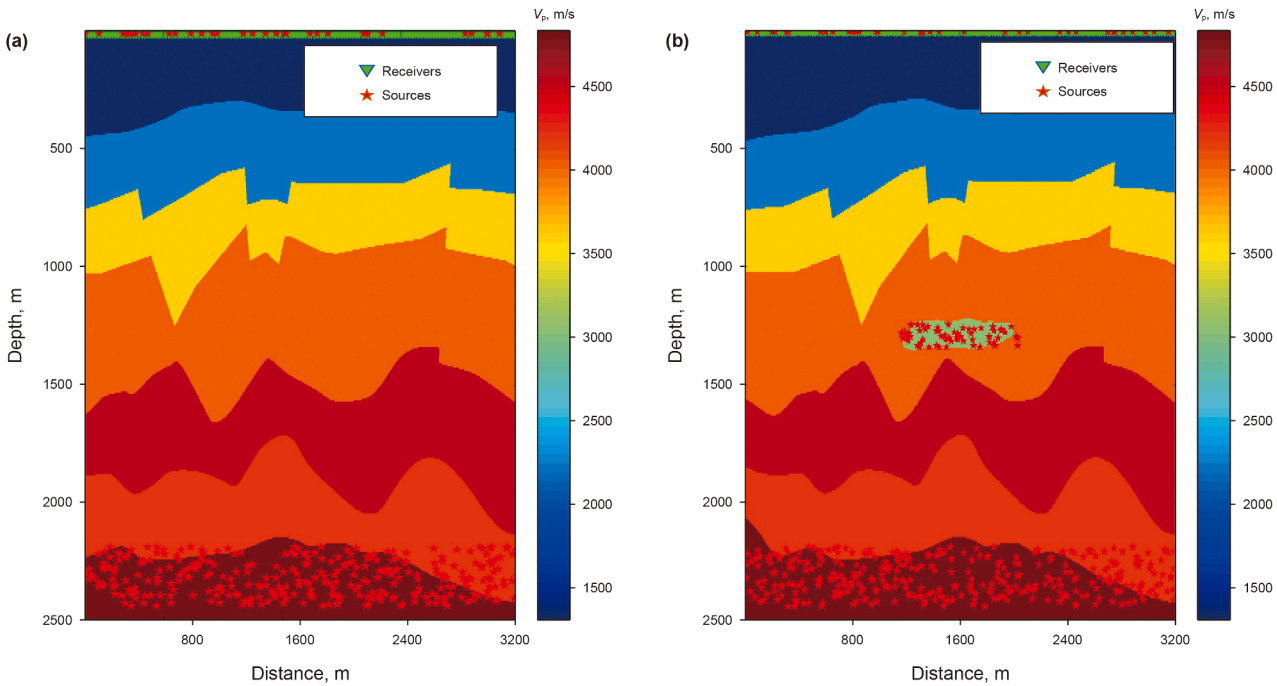


Fig. 6. 2D theoretical P-wave velocity model before (a) and after (b) gas injection.

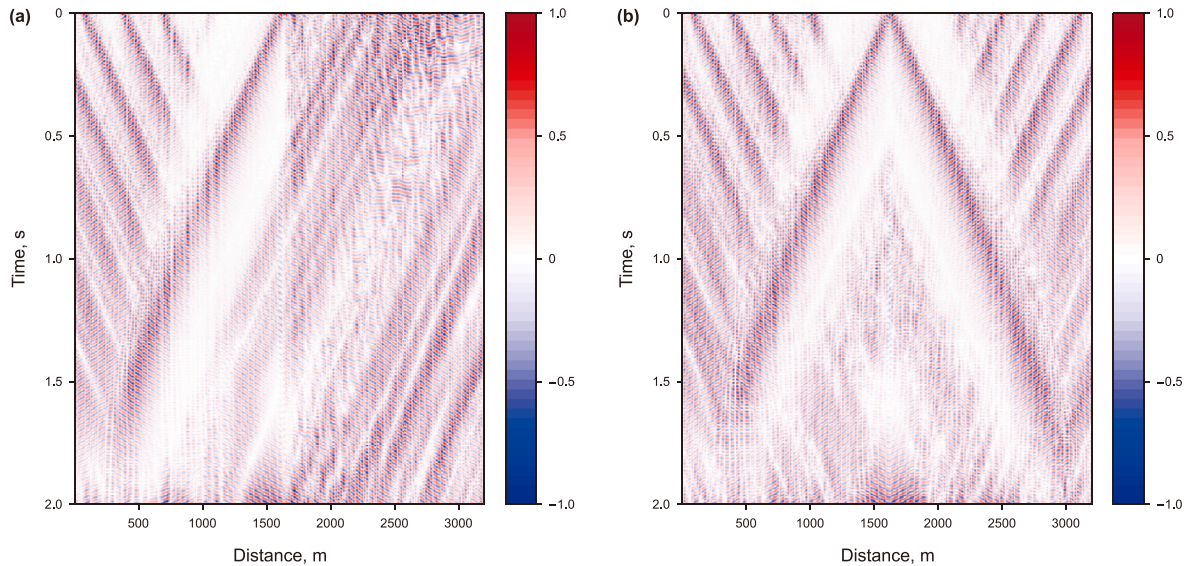


Fig. 7. Reconstructed virtual shot records before (a) and after (b) gas injection by traditional cross-correlation SI method before data screening.

$$\begin{aligned}
 (\theta_1^*, \theta_2^*, \theta_3^*) = & \arg \min_{\theta_1} \text{MAELoss}(y, f(x; \theta_1)) \\
 & + \arg \min_{\theta_2} \text{MAELoss}(y, f(x; \theta_2)) \\
 & + \arg \min_{\theta_3} \text{MAELoss}(y, f(x; \theta_3)) \quad (3)
 \end{aligned}$$

where x is the network input, θ_1 and θ_2 are the model parameters of the two channels respectively, θ_3 is the parameters of the entire SBA network model, y is the actual label, P_1 is the output result of channel 1, P_2 is the output result of channel 2, and P_3 stands for the final output of the SBA network.

2.3. Construction and training of dataset

Training using the network in Fig. 2 requires the construction of a suitable dataset. Due to the huge cost of obtaining standard labels in filed data, this paper mainly uses synthetic data for training. In practical applications, add a small amount of sparsely collected field data for fine-tuning. In order to ensure the diversity of training data and allow the model to be effectively applied to seismic data from different geographical areas, this paper uses the more complex Marmousi and Overthrust models to establish the data set and simulates a variety of distribution of underground

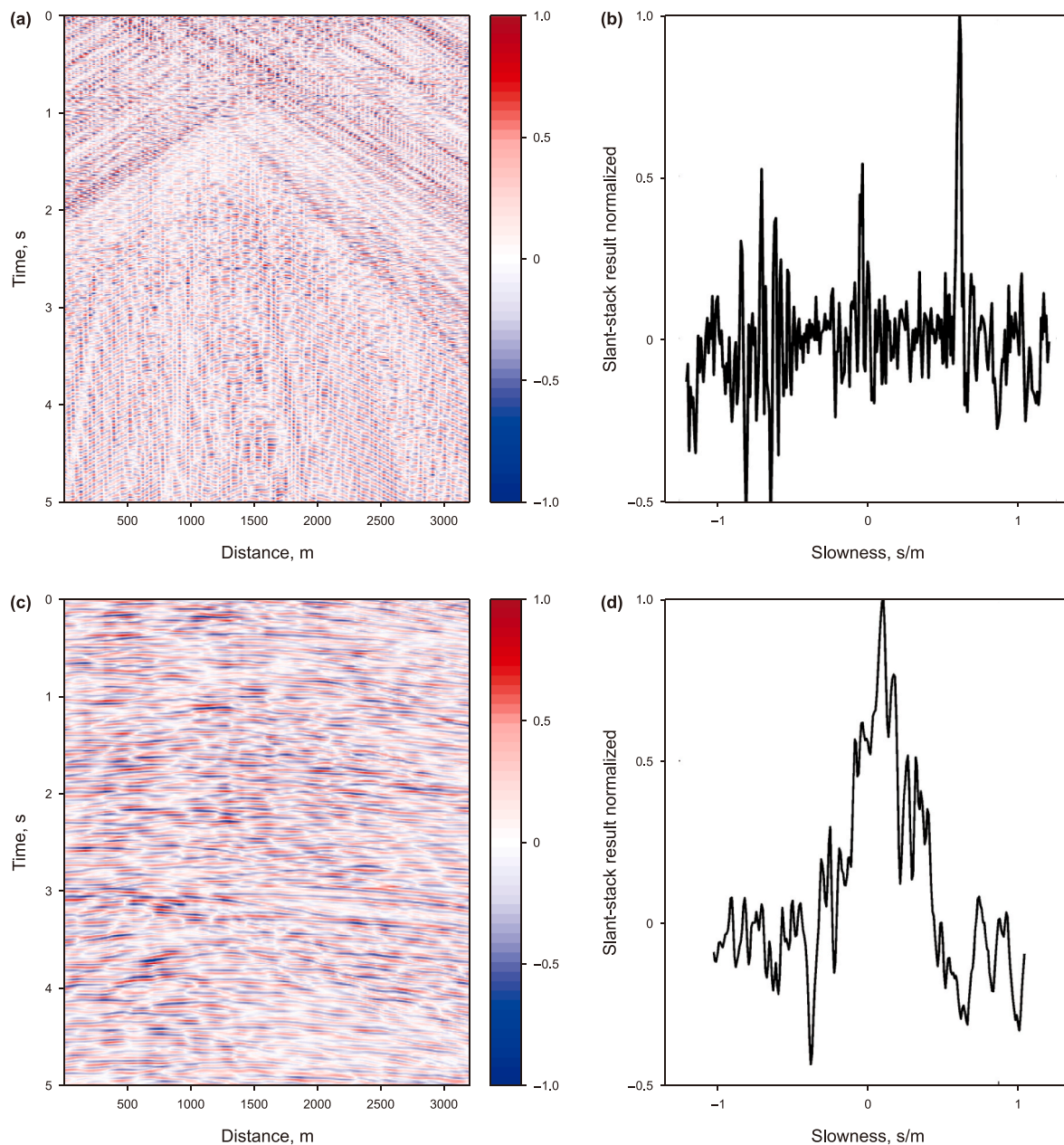


Fig. 8. Poor quality segment dominated by other waves (a) and corresponding illumination diagnosis results (b). Good quality segment dominated by body waves (c) and corresponding illumination diagnosis results (d).

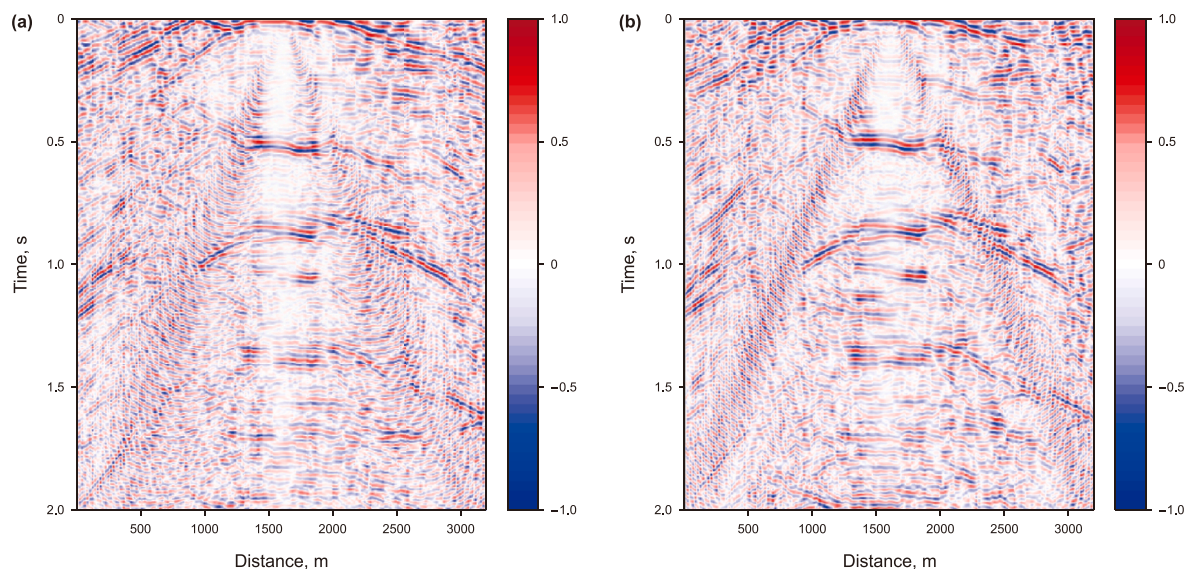


Fig. 9. Reconstructed virtual shot records before (a) and after (b) gas injection by traditional cross-correlation SI method after data screening (network input).

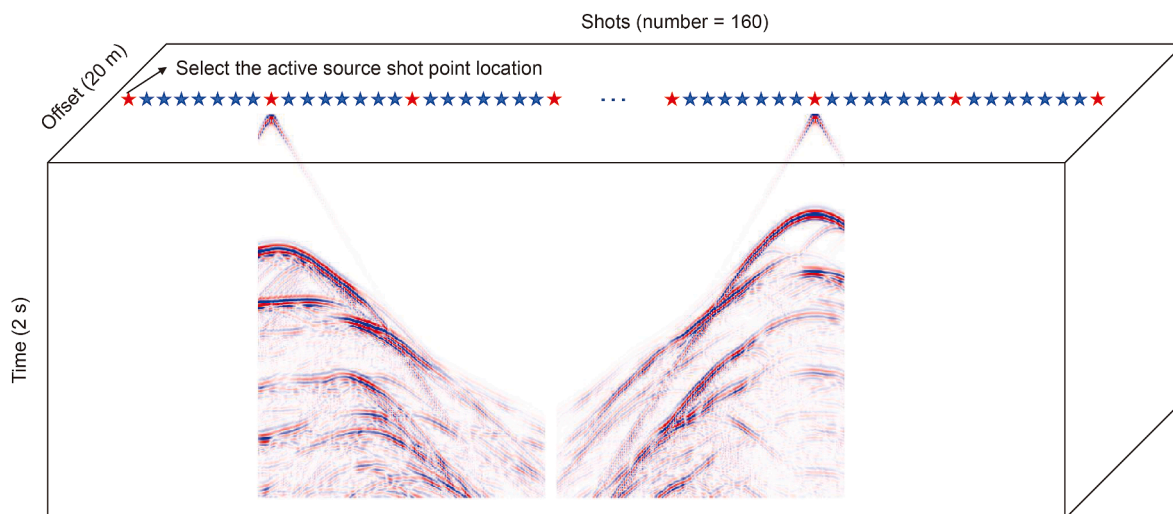


Fig. 10. Labels-Active source shot records acquired during the first period for fine-tuning (the red star indicates the selected shot point location-20 shots in total).

sources. As shown in Fig. 3, 500 sources are randomly distributed underground in the Marmousi and Overthrust, and a total of 12 models are generated (Only six seismic source distributions of the Marmousi model are shown). These six types of seismic source distributions basically cover most of the situations that exist in reality. Our motivation for doing so is mainly to expand the training dataset and make it applicable to more scenarios. In order to make the network model better applied to real data, the theoretical observation system is consistent with the field collection observation system. 160 evenly distributed receivers are arranged on the surface to continuously records environmental noise. The receiver interval is 20 m and the sampling interval is 4 ms. This experiment uses the two-dimensional (2D) finite differences elastic wave field simulation. The source wavelet has a Ricker wavelet with a central frequency of 35 Hz. Each model simulates a passive source seismic records with a duration of 1 h through the passive source observation system to construct the dataset. First, we generate the real virtual shot records of 320 shots (active source shot) with a records time of 2 s for the Marmousi and

flipped Overthrust models using the receiver as the virtual source position. Then, as shown in Fig. 4, we divide the long-term noise records into 5 s long segments, and use the reconstructed virtual shot records from 2-min long data by traditional cross-correlation SI method as input, and the corresponding active source shot gathers as output, thus obtaining a total of 14400 pairs of different training samples. 80% of the entire dataset is used as the training set, the remaining 10% is used for verification, and 10% is used for testing. It is worth noting that in order to accurately upsample the data, the actual input time dimension of the network is $nt = 512$ (fill the position beyond 500 with zero) and the distance dimension is $nx = 160$. All data is standardized before being fed into the network:

$$\hat{x} = 2 \times \frac{x - \min(x)}{\max(x) - \min(x)} - 1 \quad (4)$$

$\hat{x}$ here represents standardized data and x represents original data. In addition, to measure the overall performance of the proposed

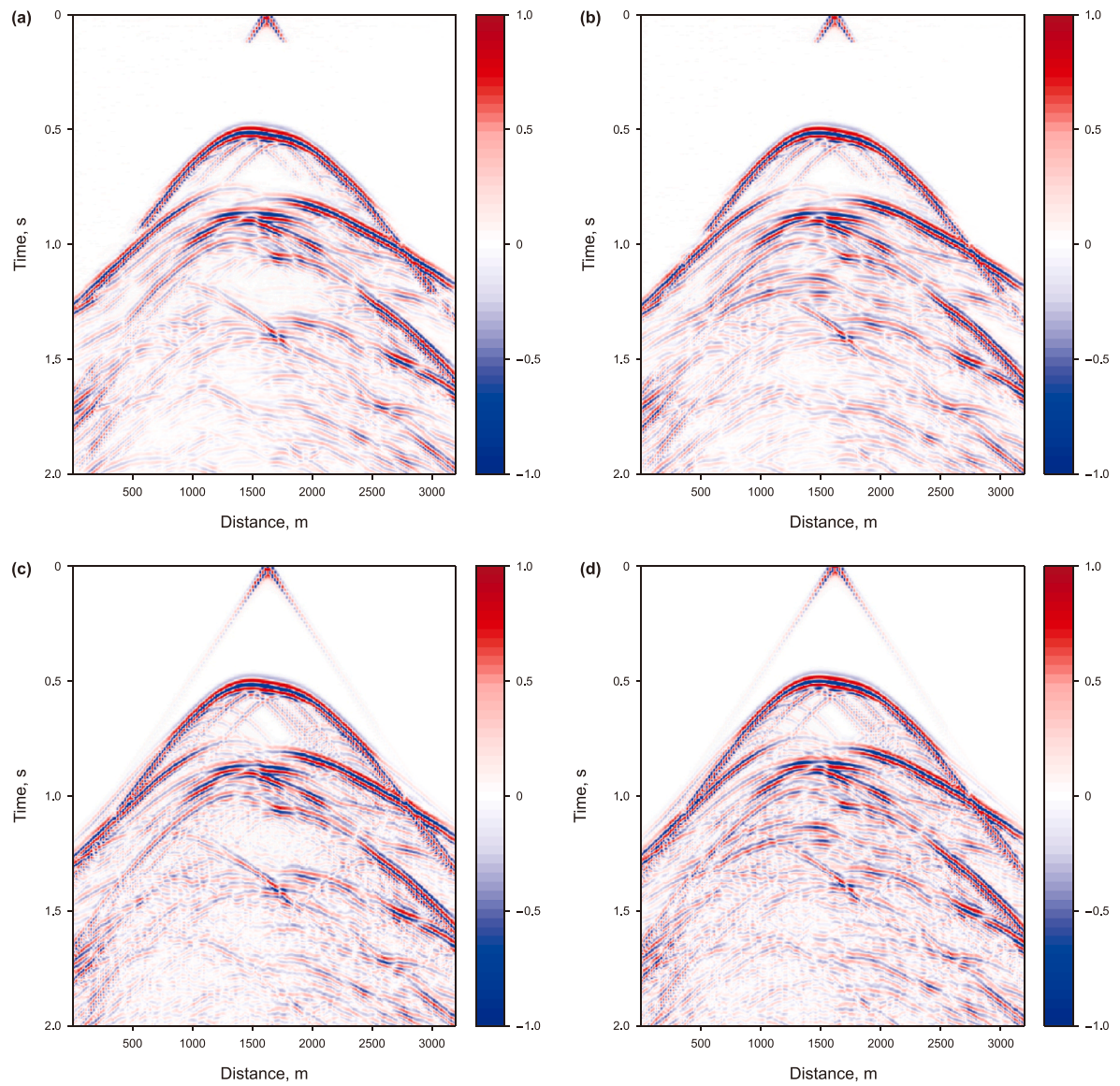


Fig. 11. Reconstructed virtual shot records before (a) and after (b) gas injection by SBA network. Real active source shot records before (c) and after (d) gas injection.

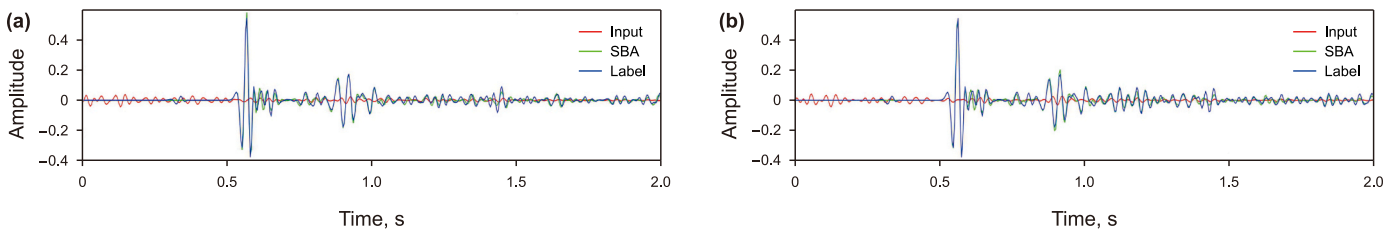


Fig. 12. (a) Comparison of the 60th trace before gas injection. (b) Comparison of the 60th trace after gas injection.

Table 3
Comparison of SBA predicted result and label in gas injection model.

Method	AMSE	PCC
Traditional SI (input)	0.01645	48.76%
SBA	0.00004	97.98%

method, we also introduced two evaluation indicators: average mean square error (AMSE) and Pearson correlation coefficient (PCC). AMSE is used to calculate the average error between the network reconstruction result and the label, and PCC is used to calculate the overall similarity between the network reconstruction result and the label, which can be expressed as:

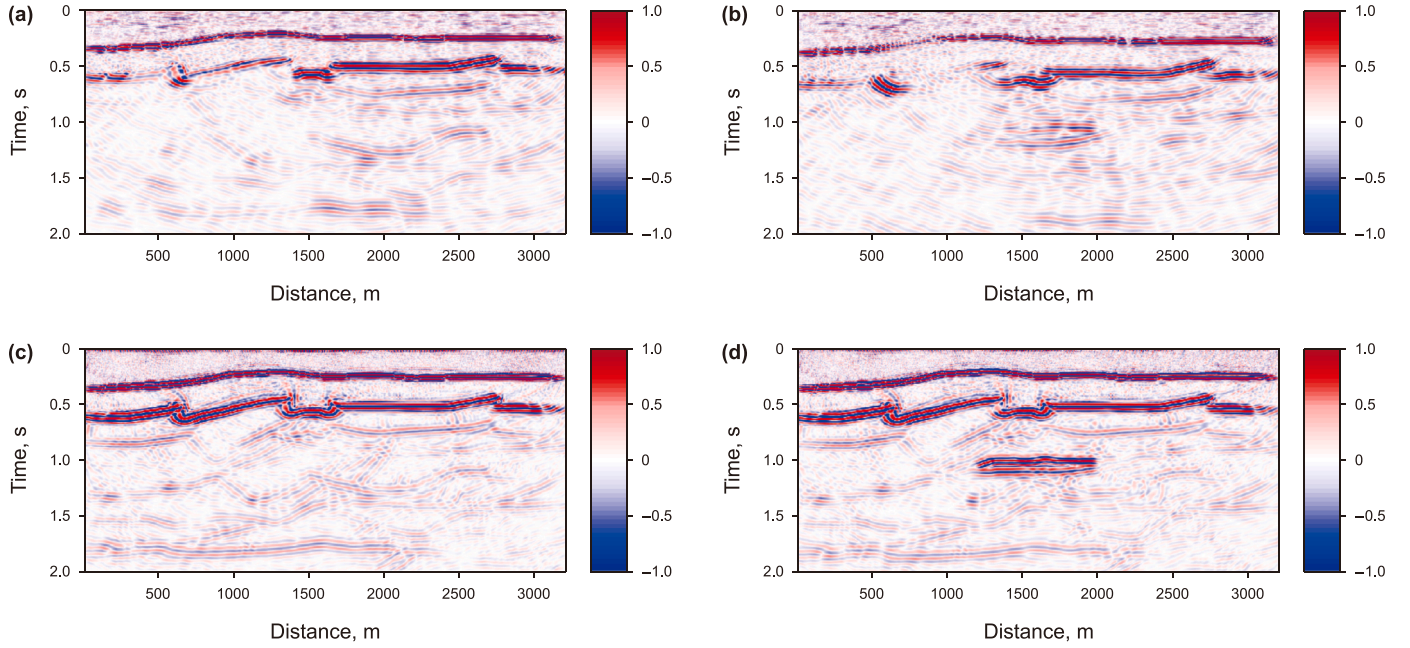


Fig. 13. RTM imaging results of reconstructed virtual shot records obtained using the traditional cross-correlation SI method: (a) before gas injection and (b) after gas injection. RTM imaging results of reconstructed virtual shot records obtained using the SBA network approach: (c) before gas injection and (d) after gas injection.

$$\left\{ \begin{array}{l} \text{AMSE} = 1/n \times \sum_{i=1}^n (y_{\text{pred}_i} - y_{\text{true}_i})^2 \\ \text{PCC} = \frac{\sum_{i=1}^n (y_{\text{pred}_i} - \bar{y}_{\text{pred}})(y_{\text{true}_i} - \bar{y}_{\text{true}})}{\sqrt{\sum_{i=1}^n (y_{\text{pred}_i} - \bar{y}_{\text{pred}})^2} \sqrt{\sum_{i=1}^n (y_{\text{true}_i} - \bar{y}_{\text{true}})^2}} \end{array} \right. \quad (5)$$

where y_{pred} is the network prediction data, and y_{true} is the real label data, $\bar{y}_{\text{pred}}$ and $\bar{y}_{\text{true}}$ are the means of y_{pred} and y_{true} , respectively.

3. Experiments

3.1. Theoretical data test

After the network completes training, we send 10% of the test data to the network for prediction. Next in Fig. 5, we show the traditional cross-correlation SI method results of short-term passive seismic data, the traditional cross-correlation SI method results of long-term passive seismic data, the prediction results generated by the deep learning model and the true virtual shot (active source) records. As can be seen from Fig. 5, the prediction results of SBA show remarkable consistency with the real virtual shot records in terms of structure and characteristics, and the reconstruction error is relatively small. In addition, to validate the superiority of the proposed SBA network framework, we conducted a series of ablation experiments and compared them to the test sets. Table 2 shows the test results of virtual shot records reconstructed from different network models. From the quantitative indicators, the SBA networks have better reconstruction effects than single networks and spatial attention mechanisms play an important role. It should be noted that due to SBA having more training parameters, the time cost consumed will increase. When using a GPU with stronger performance, significant relief can be achieved. When computing resources are limited, it is

recommended to optimize the network and training computation through gradient pruning and exploring shared parameter mechanisms.

To verify the feasibility of the method in time-lapse monitoring of passive sources, two new theoretical models were developed to simulate the process before and after gas injection in the storage reservoir, generating different noise data for testing. Since injecting gas into the ground is a complex process, this study focuses on restoring virtual shot records at different times, thus greatly simplifying the modeling process. Only simple velocity changes are used to replace the underground changes before and after gas injection. Fig. 6(a) shows the original model and Fig. 6(b) shows the model after gas injection (the P-wave velocity in the target gas injection area decreased by 600 m/s). It should be noted that choosing 600 m/s is only to make the abnormal response more obvious and facilitate the observation of reconstruction results. In the appendix, we present the reconstruction results when the speed change is smaller.

To better simulate the real underground conditions, 500 sources are randomly distributed at the surface (generating noise such as surface waves), injection location, and the bottom of the model, and the rest of the observation conditions are consistent with the Marmousi model, and the passive-source seismic records with a duration of 1 h each are simulated. Then, the long-term noise records are divided into 5 s long segments, and all segments are cross-correlated and stacked to obtain the passive source virtual shot records as shown in Fig. 7. Due to the influence of surface noise sources, compared with the real virtual shot records, the obtained virtual shot records are basically occupied by noise such as surface waves, the effective event axis is basically blurred, and no effective signal can be seen. Therefore, we first use the illumination diagnosis (Almagro Vida et al., 2014; Chamarczuk et al., 2019) method to retrieve segments containing body wave events, and a total of 205 body wave events are retrieved. The main principle is based on the difference in propagation speeds between body waves and surface waves in the study area. By setting the slowness parameter limit, it is determined whether the correlated

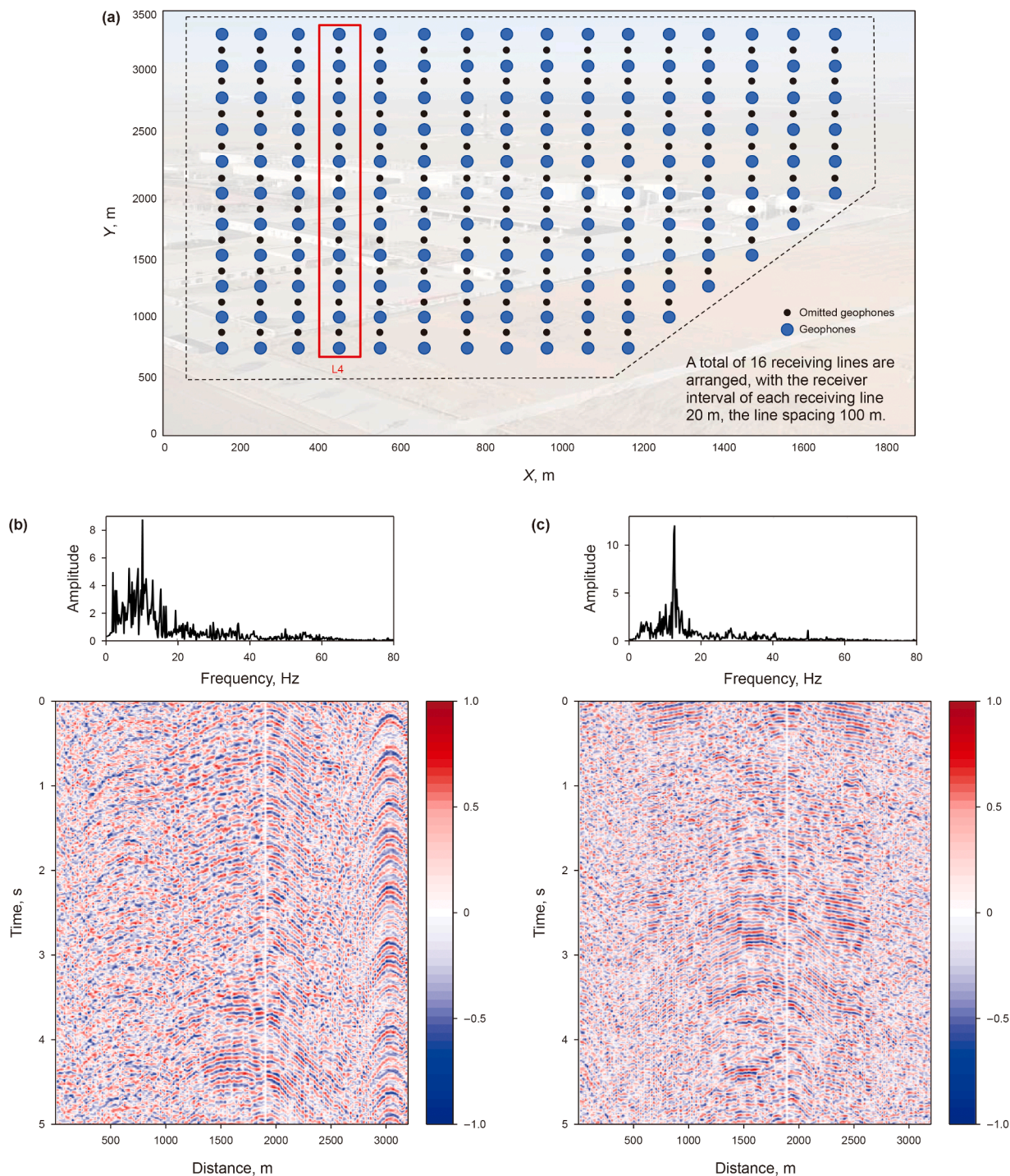


Fig. 14. (a) Actual observation system. (b)–(c) Raw data and corresponding spectrum at different time periods.

noise segment is dominated by body waves. Fig. 8 shows the noise segment dominated by body wave events and the noise segment dominated by surface wave noise identified by the illumination diagnosis method. (The absolute value of the slowness corresponding to the energy peak of the segment dominated by the body waves is smaller, that is, the peak appears in the middle area.) In Fig. 9, the reconstructed virtual shot records reflection signals after retrieval are recovered, but the resolution and SNR are not as good as those of the active source records due to the acquisition time and the distribution and number of seismic sources. Then, they are fed into the network for generating high-quality

reconstruction results. As shown in Fig. 10, to better reconstruct the virtual shot records, we add the active source shot records of different positions of the 20 shots before steam injection (which corresponds to a small amount of sparsely collected active source data in the early period of the actual monitoring process) into the network for training and fine-tuned the trained model. It is worth noting that the positions of the selected active source shot records should cover the entire acquisition space as evenly as possible. If only active source shot records in a fixed area are selected, the reconstruction results will be affected. This paper uses an equidistant selection scheme. Of course, in theory, the denser the

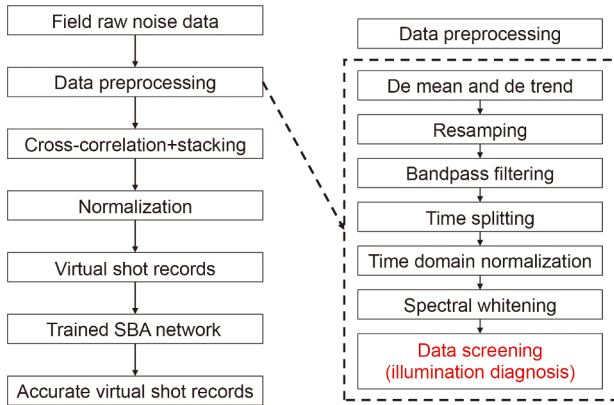


Fig. 15. Flowchart of the process for accurately reconstructing virtual shot records.

acquisition, the more active source shot records are used, and the better the reconstruction effect.

In Fig. 11, we compare the reconstructed virtual shot records by traditional cross-correlation SI method after retrieval, the prediction results generated by deep learning, and the real virtual shot records. However, there are certain differences between the network's prediction results and the actual virtual shot records. But satisfactorily, the prediction results of the deep learning model can be seen that effective reflection signals are retained, and are closer to the real virtual shot records, and the reconstruction quality is improved. For further comparison, we extract single trace records for comparison (Fig. 12). We can see the consistency between the predicted data and the label data, which strongly demonstrate the excellent performance of the proposed method in the task of reconstructing virtual shot records. The evaluation results are shown in Table 3.

Finally, to verify the prediction results further, we will process and image the reconstructed virtual shot records after retrieval and the virtual shot records predicted by the SAB network. The imaging results of the two data are shown in Fig. 13. The imaging

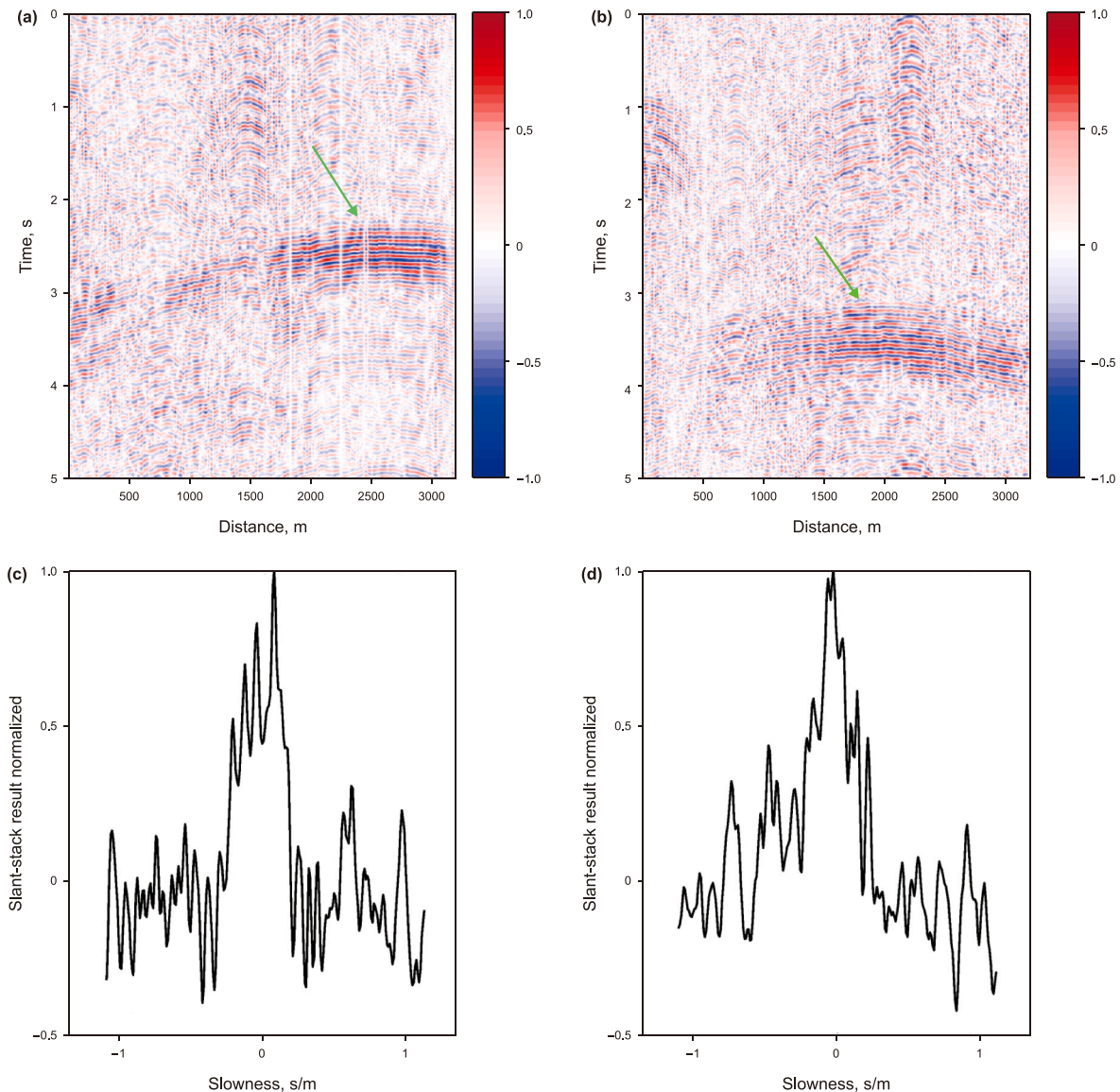


Fig. 16. (a)–(b) Different high-quality segments containing clear body wave (green arrows are body wave events) and (c)–(d) corresponding illumination diagnosis results.

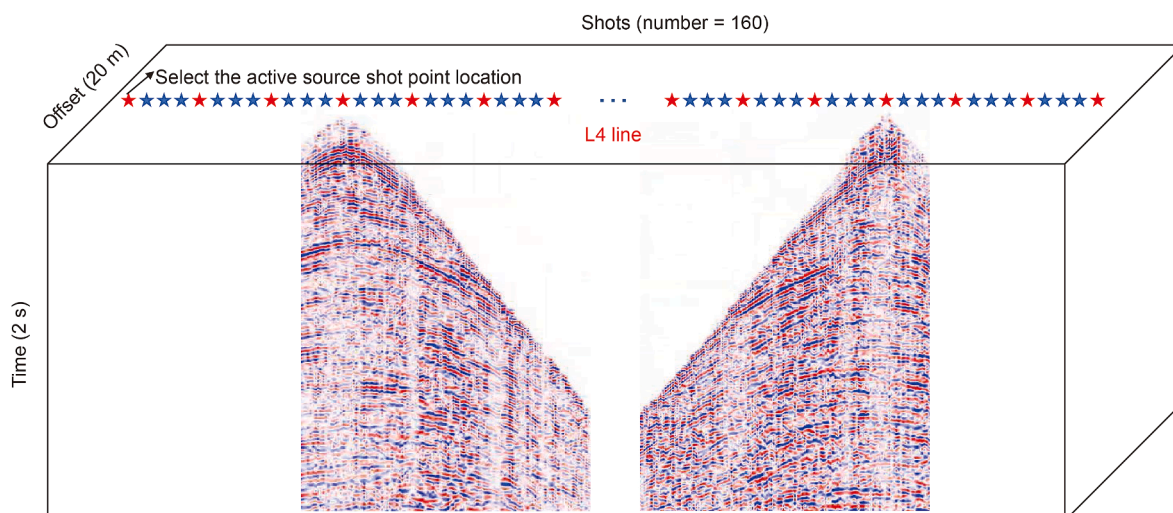


Fig. 17. Labels-Active source shot records acquired during the first period for fine-tuning (the red star indicates the selected shot point location-40 shots in total).

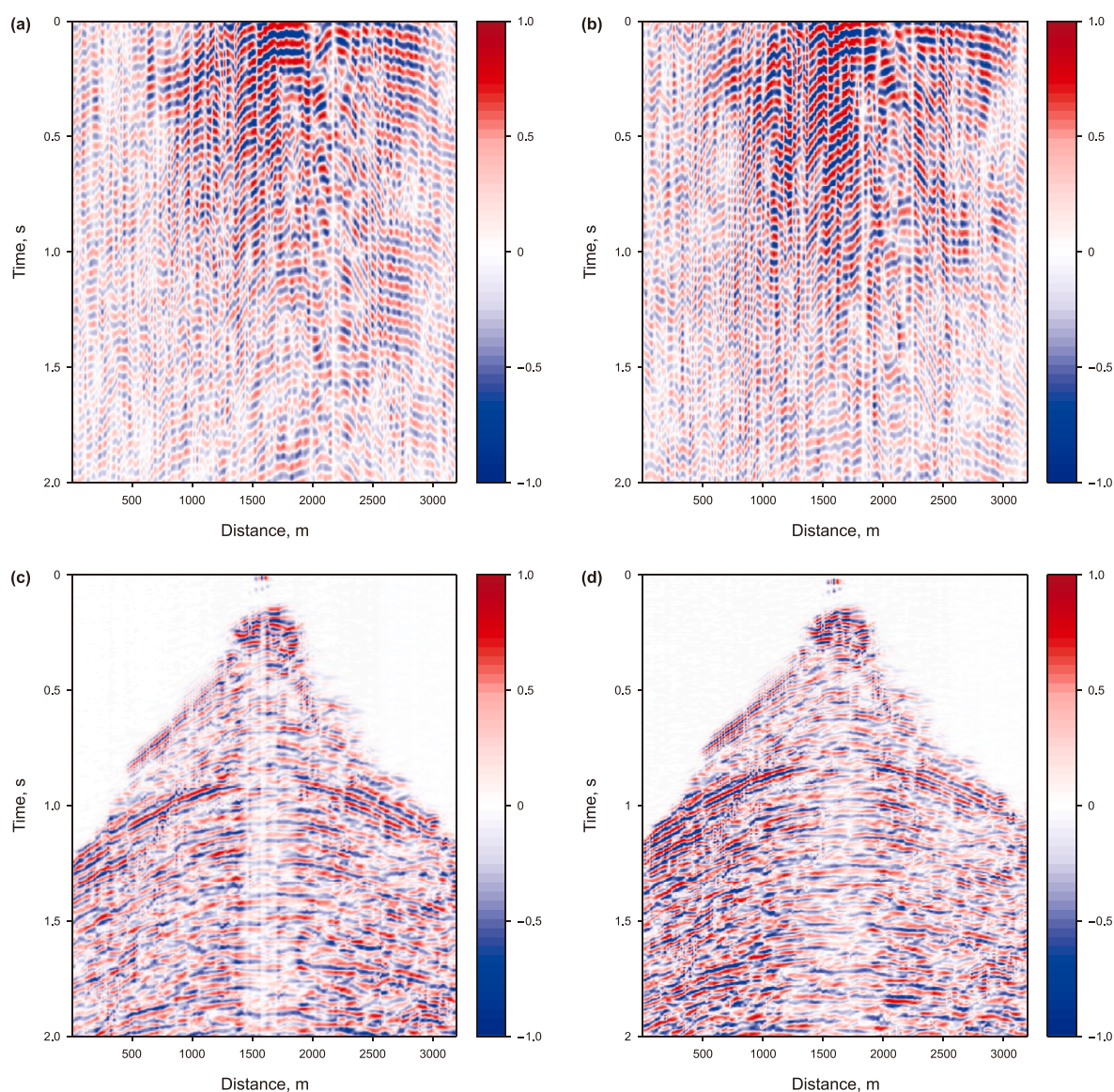


Fig. 18. Reconstructed virtual shot records on September 4th (a) and October 3rd (b) by high-quality segments and traditional cross-correlation SI method. Reconstructed virtual shot records on September 4th (c) and October 3rd (d) by SBA network.

quality is improved, and abnormal areas that have changed can be clearly discovered, providing reliable information for passive source time-lapse monitoring. Experimental results demonstrate the advantages of deep learning method in dealing with these complex nonlinear problems. Compared with traditional method, our method can recover higher-quality virtual shot records from situations where the effective data acquisition time is limited or data quality is poor, demonstrating its wide applicability.

3.2. Field data test

Encouraged by the application results of theoretical data, we further applied this method to the reconstruction of virtual shot records of field background noise data to verify its effectiveness and practicality. This data is collected via a three-dimensional linear arrangement for a gas storage project in Northwest China, and its observation system is shown in Fig. 14(a). There are 16 receiving lines, the sampling interval is 1 ms, the receivers interval of each line is 20 m, and the collection time is several months. We select 12 h data of two days in different collection time periods of the L4 line (a total of 160 geophones) after the start of gas injection for experiments. The acquired raw data and its corresponding frequency domain characteristics are shown in Fig. 14(b) and (c). It can be seen that the SNR of the original data is relatively low, the main frequency band is concentrated in 0–30 Hz, the spectrum

changes more dramatically, and 0–10 Hz is mostly useless low-frequency noise. In order to improve the SNR of the data and make the data useable for subsequent imaging, as shown in Fig. 15, we proposed a preprocessing process suitable for the task of this paper based on Bensen et al., 2007. In this paper, we divide the long-term noise data into 5 s long segments, the data is resampled from 1 ms to 4 ms, and the frequency band of the bandpass filter is 10–30 Hz. Next, the illumination diagnosis method is used to retrieve the segments containing body wave events from the original data. Due to the complex acquisition environment and low SNR data, we only retrieve 396 segments from 17280 with obvious body wave energy. In Fig. 16, we show the retrieved high-quality segments containing clear body waves. Subsequently, we feed the virtual shot records reconstructed from the retrieved data into the network to further improve its quality. Similarly, as shown in Fig. 17, to better reconstruct the virtual shot records, we add the active source shot records of 40 shots at different positions on the L4 line before the start of gas injection and sent them to the network training to fine-tune the trained model.

In Fig. 18, the prediction results show that the SNR and resolution of the network's reconstruction results have been improved. In order to verify the accuracy of the network reconstruction results, we further process and image the reconstructed virtual shot records traditional cross-correlation SI method after retrieval and the virtual shot records predicted by the network, and compared

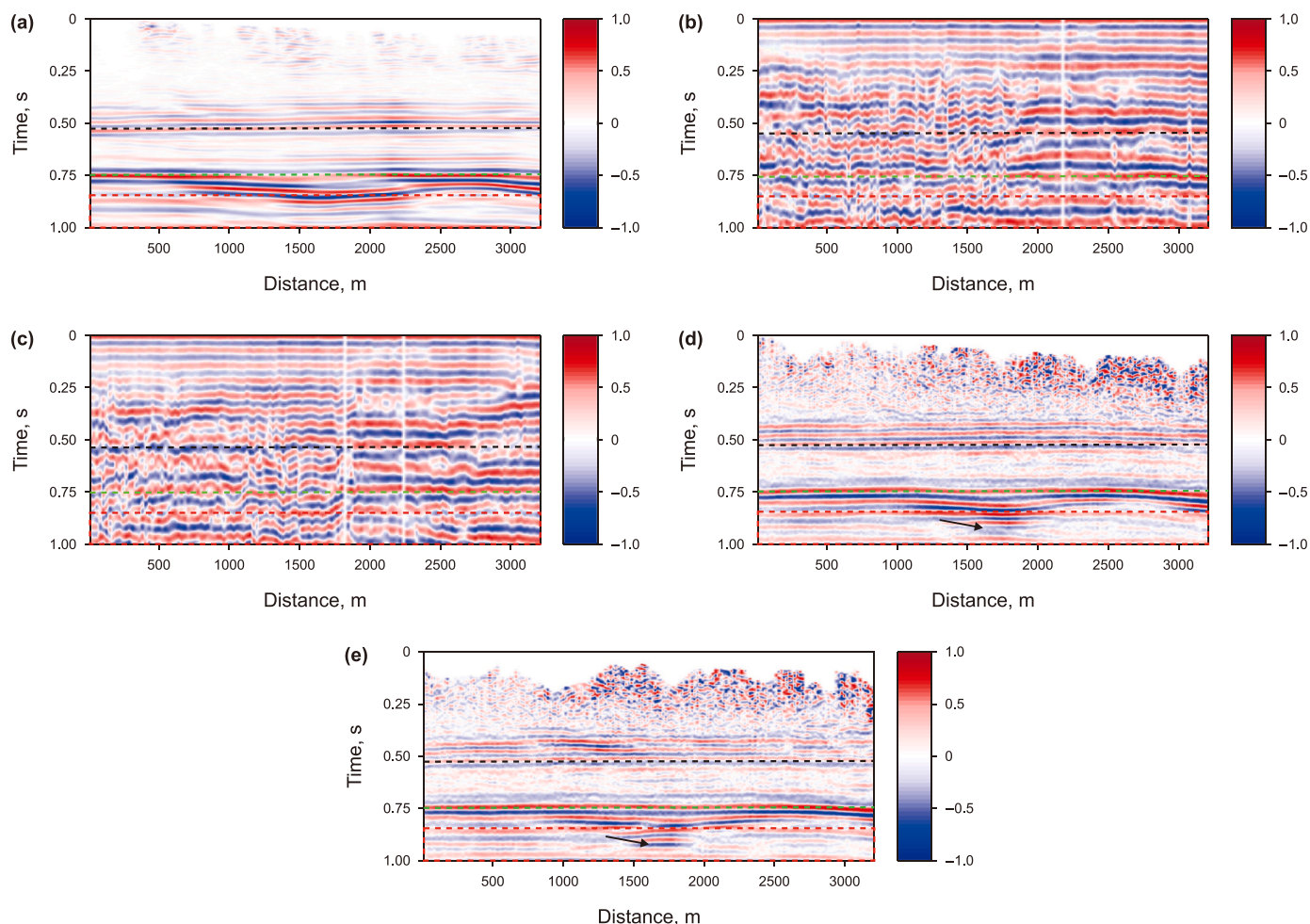


Fig. 19. (a) Field active source post-stack imaging results. Reconstructed virtual shot records post-stack imaging results on September 4th (b) and October 3rd (c) by high-quality segments. Reconstructed virtual shot records post-stack imaging results on September 4th (d) and October 3rd (e) by SBA network.

them with the active source post-stack profile before injection (Fig. 19). In the active source seismic profile, different colored lines are used to mark the moment when the strong amplitude event occurs, and the lines are projected to the corresponding position of the passive source profile. The red box area indicates the approximate location of the gas storage area between 0.8 and 1 s and the reservoir depth is about 1 km. On the whole, the projection of the lines positions in Fig. 19(b) and (c) are consistent with the strong reflection axis of the active source profile. However, due to the dominant frequency band of the passive source monitoring data being lower, there is a big difference in resolution from the active source profile. It is difficult to see specific changes in the reservoir area from the imaging section. It can only be seen that the imaging results of the two days have changed the in-phase axes at the red box area. In Fig. 19(d) and (e), on the contrary, it is exciting that the network reconstructed passive source profiles have higher resolution, and the projections correspond better to the position of the in-phase axes in the active source profiles, and are more consistent with the active source profile, indicating the reliability of the imaging results. Finally, we perform a time-lapse analysis of the network imaging results of the L4 line for two days. In Fig. 19, the imaging results of the two days are basically consistent in the shallow event axis. In the red area, there are obvious differences in the imaging results, showing the impact of gas injection on the gas storage area, where the imaging results of the reconstructed virtual shot records by the SBA network seem to indicate clearer changes.

4. Conclusions

To overcome the time limit of noise recording and the spatial limit of underground source distribution required in seismic interferometry, this paper proposes a passive source virtual shot records reconstruction method based on the SBA network, and applies it for the first time to field data. It allows accurate reconstruction of passive source virtual shot records from short-term noise segments containing body wave events. Compared to a single network model, the special network structure allows the network to capture more spatial and temporal features simultaneously, and the quantitative indicators demonstrate its superior performance in reconstructing virtual shot recording task. Experiments with theoretical and practical data show that the model trained with data generated from the complex theoretical models and fine-tuned with a small amount of first period active data is suitable for accurate reconstruction of the virtual shot records in other scenarios. Compared with traditional SI methods, it greatly improves the SNR and resolution of the virtual shot records, and lays a solid foundation for the subsequent time-lapse imaging and monitoring. It is worth noting that the input data should contain valid body wave events as much as possible to ensure that the

network can accurately reconstruct the Green's function. In addition, this method also requires the use of partial active source data for training to achieve ideal results. On this basis, the method can be applied to various scenarios and has enormous application value. Of course, this method also has the problem of single characteristics of the training input data. The input of multiple information may help the network to better reconstruct the virtual shot records, which is worthy of further study.

CRedit authorship contribution statement

Ying-He Wu: Writing – original draft, Software, Methodology. **Shu-Lin Pan:** Writing – review & editing, Resources, Funding acquisition. **Kai Chen:** Methodology, Data curation, Conceptualization. **Yao-Jie Chen:** Visualization, Validation. **Da-Wei Liu:** Writing – review & editing, Supervision. **Zi-Yu Qin:** Project administration, Investigation, Funding acquisition. **Sheng-Bo Yi:** Validation, Project administration, Formal analysis. **Ze-Yang Liu:** Supervision, Investigation.

Conflict of interest

The authors declared that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix A

To verify the reconstruction effect of the proposed method on time-lapse virtual shot records after small velocity disturbances, we added theoretical experiments when the velocity is reduced by 200 m/s. Using the same training process, the experimental results are as follows.

Comparing the active source shot records in Fig. 20(c) and (d), when the velocity decreases by 200 m/s, the time-lapse response caused by velocity changes is small, but SBA can still reconstruct high-quality virtual shot records, presenting the time-lapse response caused by velocity changes. For further comparison, we extracted single trace records for comparison (Fig. 21), the predicted data is relatively close to the labeled data. The experimental results show that the proposed method can still accurately recover the time-lapse virtual shot records when the underground velocity has no significant change.

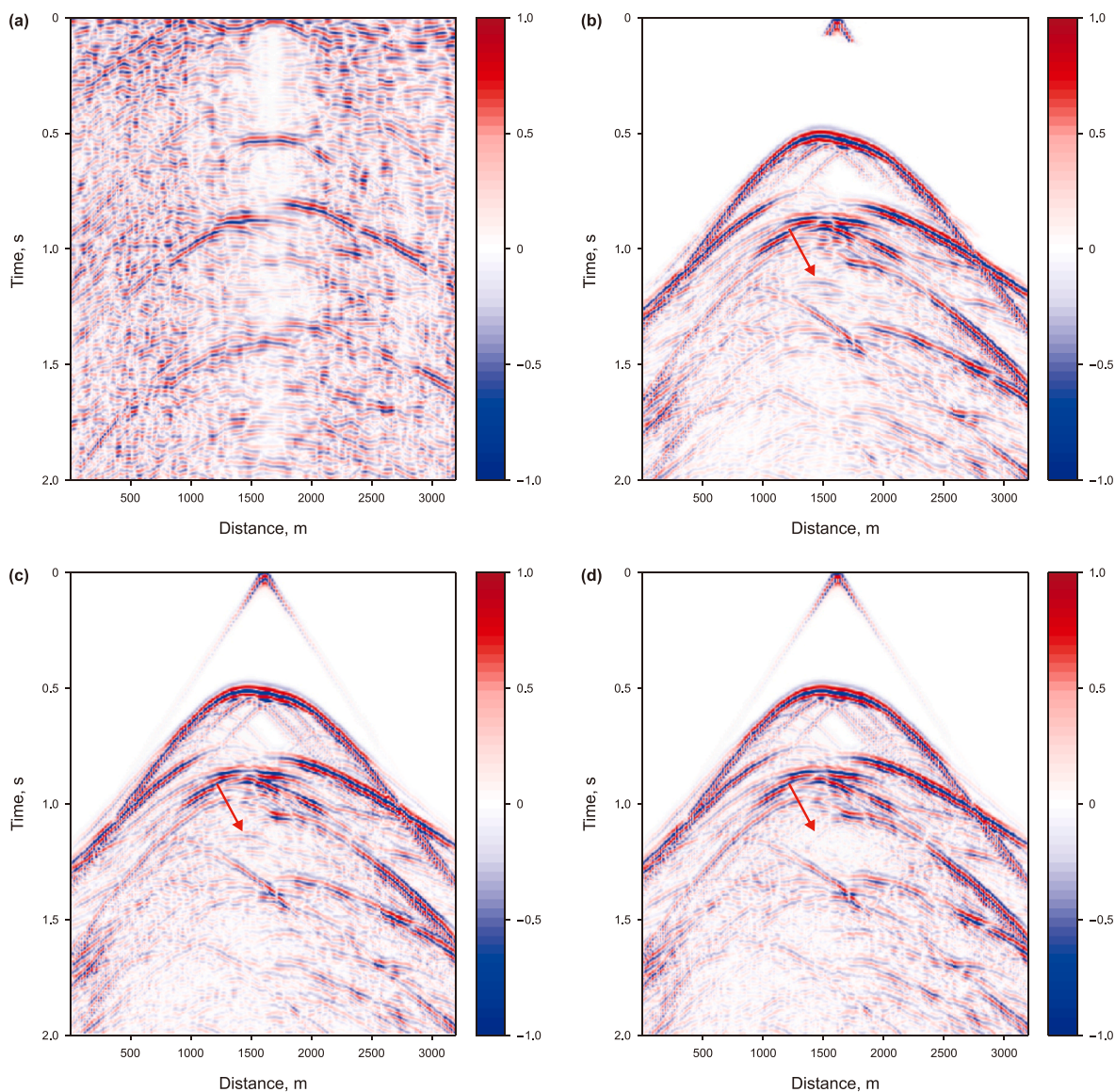


Fig. 20. (a) Reconstructed virtual shot records by traditional cross-correlation SI method (Network input). (b) Reconstructed virtual shot records by SBA network. (c) Active source shot records with velocity reduced by 200 m/s after gas injection. (d) Active source shot records before gas injection.

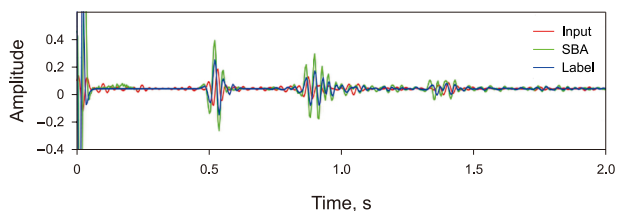


Fig. 21. Comparison of the reconstruction results for the 80th trace record.

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