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Hierarchical division encoder–decoder network for distributed acoustic sensing-vertical seismic profile noise suppression

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Abstract

In recent years, traditional geophones for well seismic data acquisition have progressively been replaced by distributed acoustic sensing (DAS), a novel technique. The primary attributes of DAS are its extensive well coverage and robust adaptability to challenging acquisition situations. Unlike conventional geophones, vertical seismic profile (VSP) data obtained using DAS exhibit lower signal-to-noise ratios (SNRs) and more complex noise types. These complex and energetic perturbations pose challenges for further data analysis. Contemporary methods for mitigating noise in DAS-VSP data sometimes fail to yield complete and precise information, leading to inferior denoising quality and diminished signal recovery. We propose a hierarchical division encoder–decoder network utilizing a convolutional neural network to address this issue. This network employs spatial attention techniques for systematic reconstruction and facilitates hierarchical feature extraction according to information scale. Our methodology provides superior noise reduction capabilities while preserving signal integrity. It achieves this by comprehensively addressing features at all scales. Additionally, we generated the required training set by combining synthetic data with real noise, as no publicly available training sets are available for DAS-VSP data. The trained denoising network processes and analyzes both synthetic and real recordings. The experimental results demonstrate the efficacy of this technique in eliminating various types of DAS-VSP noise while preserving signal amplitude integrity and ensuring continuity of signal recovery.

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1. Introduction

Seismic exploration is advancing into deeper, more complex geological settings as surface resources are exhausted.^{1–3} This depletion results from the extensive extraction of oil and other material resources. The seismic wave reflected from deep depths is

significantly attenuated by wave propagation phenomena such as geometrical spreading and attenuation, as well as the gradual deterioration of the acquisition environment, making it nearly inaudible amid ambient noise.⁴ The effective signal is considerably disrupted by overlapping interference from multiple sources. The reliability of seismic data is therefore compromised. It is imperative to use more effective acquisition technology. The technology of distributed acoustic sensing (DAS), which uses optical fiber as the sensing medium rather than an electric geophone, has advanced steadily.^{5,6} By extracting and demodulating interferometric signals generated by phase fluctuations of Rayleigh scattered light, DAS enables the quantitative analysis of vibration signals within a specific frequency range.^{7–9} DAS exhibits superior sensitivity in detecting weaker signals compared to conventional detectors, demonstrates enhanced resistance to electromagnetic interference, is straightforward to install, and is more cost-effective. DAS has applications in border security, reservoir monitoring, and vertical seismic profiling (VSP), owing to its acquisition and economic advantages.^{10,11}

The VSP approach provides interlayer velocity data, which are crucial for transforming seismic records from the time domain to the depth domain.¹² A geophone is utilized within the wellbore, accompanied by a surface source positioned adjacent to the well for vertical borehole measurements. Substituting conventional detectors with DAS can enhance the sampling density of borehole seismic data in VSP. Nonetheless, numerous obstacles emerge in the implementation of DAS. Noise removal is especially challenging. In DAS-acquired seismic data, signal amplitudes are much weaker than noise amplitudes. Furthermore, with DAS-VSP data, the predominant noise is generated by the device itself, whereas in geophone data, the majority of noise is derived from external sources. The noise composition of DAS-VSP data is intricate, encompassing inherent instrument noise—such as fading noise, time-varying optical noise, and horizontal noise—as well as externally generated stochastic noise. Thus, the signal-to-noise ratio (SNR) of DAS-VSP data is inferior to that of traditional geophone data owing to elevated noise levels and more complex noise attributes.^{13,14}

Contemporary research on DAS in borehole VSP primarily focuses on two areas: data gathering and data processing.^{15–17} Modifying the seismic source type and improving fiber-optic installation help mitigate noise during the acquisition phase. This method has a limited impact when confronted with aliasing noise that overlaps the frequency range of effective signals. A multitude of denoising methods have been developed for processing seismic data. The work mainly focuses on data processing.

For example, diffusion models have been applied to denoise DAS-VSP data, effectively suppressing “zigzag” noise.¹⁸ U-Net network architectures have been used to remove coupling noise, demonstrating strong signal recovery capabilities.¹⁹ In addition, multitask deep learning models have been proposed to simultaneously perform denoising, interpolation, and wavefield separation, improving data quality.^{20–24}

Initial denoising methods, including band-pass filtering, median filtering, and Wiener filtering, exploited the frequency differences between signals and noise to mitigate noise in seismic data.^{25,26} These techniques are widely used due to their simplicity; however, their effectiveness on non-stationary seismic data is limited. Time-frequency analysis methodologies have been used for denoising, such as the S-transform and time-frequency peak filtering. These methods differentiate noise components by analyzing the distinct properties of signals and noise in both temporal and frequency domains. The efficacy of time-frequency analysis is significantly influenced by parameter selection, and manual adjustments may result in inadequate differentiation between signal and noise. Multi-scale decomposition techniques aim to denoise seismic data by removing intrinsic mode functions (IMFs) linked to noise. Notable instances include empirical mode decomposition (EMD)^{27,28}, variational mode decomposition^{29,30}, and ensemble empirical mode decomposition.^{31,32} Nonetheless, considerable aliasing between signals and noise may result in their simultaneous presence within the same IMF. Consequently, maintaining or discarding a component may introduce residual noise or degrade the signal. Sparsity-based methods, such as the wavelet transform (WT), also draw attention in seismic data processing. WT transforms seismic data into a sparse representation and then applies thresholding to eliminate noise. While WT can effectively reduce noise, its efficacy is limited by subjective parameter selection and the absence of directional guidance in thresholding. Conventional denoising techniques for complex noise in DAS-VSP data, each based on different concepts, have inherent limitations.³³ Consequently, the development of more effective noise-reduction methodologies is essential.

Deep learning has become a significant research focus in recent years. They have shown substantial advancements in image processing, computer vision, speech recognition, and related fields.^{34–37} Convolutional neural networks (CNNs) have been effectively applied in various seismic exploration tasks, including fault identification, seismic inversion, and seismic data denoising.^{38–41} In seismic denoising, CNNs differentiate signals from noise efficiently by establishing a nonlinear mapping between the target signal and the

contaminated data. Traditional network architectures include supervised feedforward convolutional denoising networks (DnCNNs)⁴² and unsupervised generative adversarial networks (GANs).^{43,44} Deep learning techniques outperform conventional denoising algorithms by utilizing diverse hyperparameters to independently extract abstract information, facilitating more efficient sparse representations. Nevertheless, challenges remain. Noise reduction performance for complex DAS-VSP data may be insufficient, and using a single-scale convolution kernel in DnCNN can lead to the loss of essential information. GANs can reduce reliance on extensive training datasets by employing an adversarial framework. This framework directs the generative model to produce data consistent with the actual distribution. However, instability and convergence issues render GAN training challenging. Consequently, an ongoing investigation into more efficient network architectures is essential.

We propose a hierarchical division encoder-decoder network (HDEN) to efficiently distinguish signals from noise in DAS-VSP data. In the initial phase, convolution with a large kernel extracts fundamental features throughout the encoding process. The large kernel's extensive receptive field enhances global feature extraction, but considerably increases computational cost. HDEN employs asymmetric convolution to reduce computational expenses while preserving global feature extraction. A multi-scale method is used to enhance global features and capture more detailed information. During the decoding phase, an attention mechanism integrates diverse local features from the encoding phase and progressively refines them across multiple scales. Finally, deconvolution reconstructs the data. Due to the lack of a standardized training dataset for DAS-VSP data, we generated synthetic data using forward modeling. Environmental noise was then isolated and combined with the synthetic data to form the training set.

The rest of the manuscript comprises the following sections. In Section 2, we introduce the design principle and network structure of HDEN. In Section 3, the construction of the training dataset, which includes both the signal set and the noise set, is discussed. In Sections 4 and 5, the processing results for synthetic and field DAS data are presented to investigate denoising performance. Finally, Section 6 concludes the main findings of this study.

2. Methods

2.1. Principle of denoising

Generally, the seismic data, including DAS data, always suffer from additive noise. Thus, the expression of DAS-VSP data can be formulated as follows (Equation 1):

$$r = p + n \quad (1)$$

where p represents the clean DAS-VSP signal, while n denotes the noise component. The denoising process aims to establish a mapping relationship between noisy data r and pure signal p by simulating function F through a trained network, thereby effectively removing various types of noise, as follows (Equation 2):

$$p \approx F(r; w, b) \quad (2)$$

where w represents the weight parameters, and b represents the bias parameters. The primary objective of training is to optimize and adjust these two network parameters to remove noise while preserving signal integrity as much as possible. We guided the update of network parameters by minimizing the following loss function (Equation 3):

$$l(w, b) = \frac{1}{2T} \sum_{k=1}^T \|F(r_k; w, b) - p_k\|^2 \quad (3)$$

The denoising result of the training data r_k is represented by $F(r_k; w, b)$, while p_k represents the corresponding clean signal of r_k . Additionally, T denotes the number of training samples. During each iteration, we utilized T samples to update the network parameters and ultimately optimize them.

2.2. Structure of the denoising network

The network architecture of HDEN is depicted in Figure 1A and consists of four main components: input, encoder, decoder, and output. The input unit comprises a 7×7 convolution with a stride of 2. This layer reduces the resolution of seismic records to accelerate data processing and enhance the extraction of high-level abstract features. Unlike conventional downsampling, the input unit preserves relative quality while decreasing recorded resolution. The encoder employs a hierarchical feature coding approach guided by feedforward signals. This facilitates multi-level feature extraction and precise information encoding across scales. The decoder integrates features from every encoder level using the embedded attention mechanism. During the output phase, the decoder's features are processed by upsampling and convolution to restore resolution and channel count in the seismic record. The encoder and decoder are the fundamental components of HDEN, and their architectures will be elaborated upon subsequently.

2.2.1. Encoder

In the encoder, asymmetric convolution is applied to improve resource efficiency and reduce computational

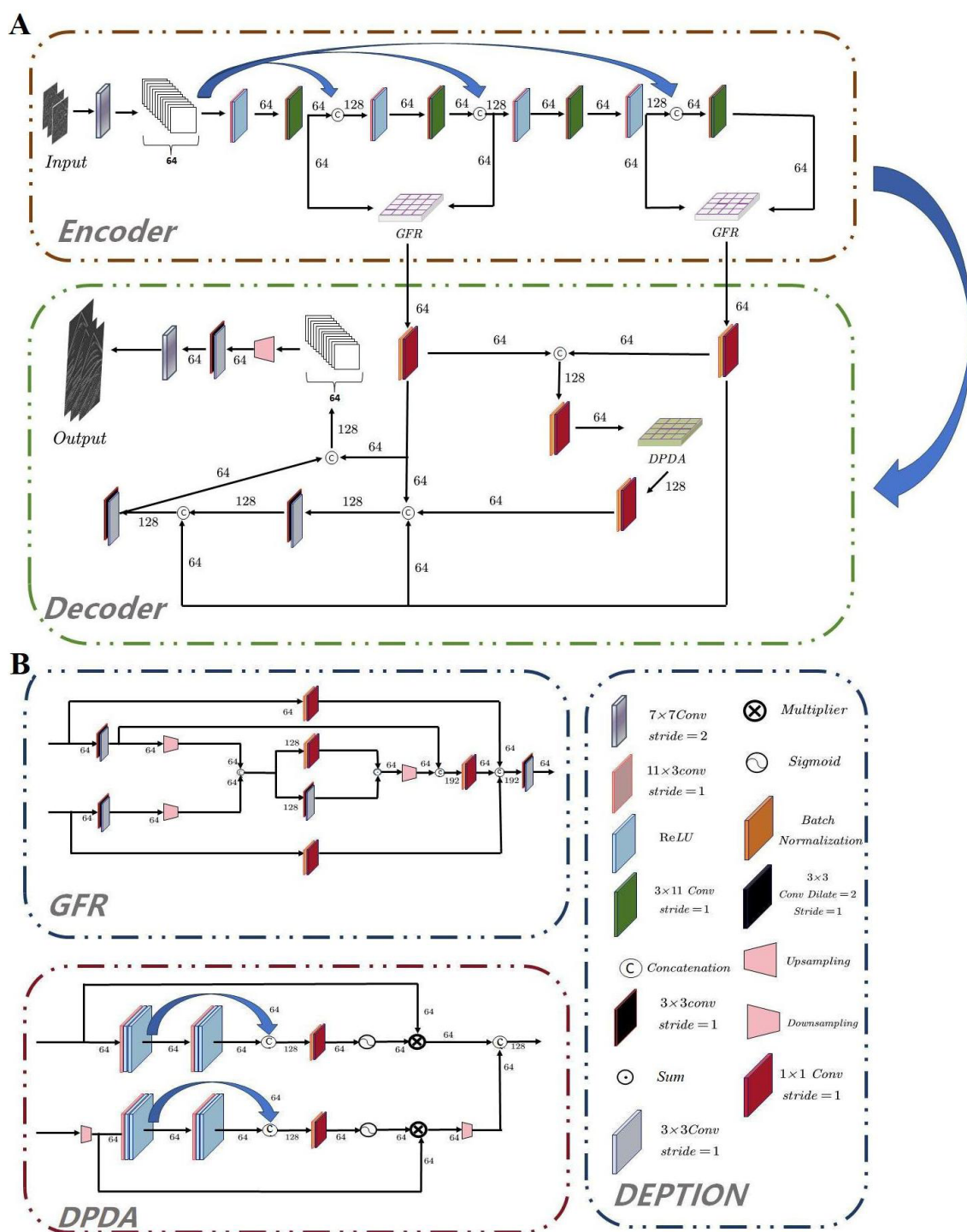


Figure 1. Hierarchical division encoder-decoder network architecture. (A) The overall structure. (B) The structure of the main network components. Abbreviations: DPDA: Dual-path dense attention; GFR: Global feature refinement; ReLU: Rectified linear unit.

burden.⁴⁵ The encoder predominantly uses a feedforward methodology to transmit information, thereby enhancing its capacity to extract novel features. Following global feature extraction, the global feature refinement (GFR) module partitions the global information obtained via asymmetric convolutions into multiple scales. This allows detailed local information to be refined across diverse scales. The GFR module effectively leverages both global and local information across hierarchical levels, thereby enhancing feature extraction precision.

2.2.2. Global feature refinement module

The GFR module achieves precise information segmentation by integrating skip connections with multi-scale feature extraction, as shown in Figure 1B. In the multi-scale component, two input datasets at different levels undergo independent 3×3 convolutions and are then downsampled to produce scales distinct from the original input. The two paths are combined and processed using standard and dilated convolutions to enhance multi-scale partitioning. After obtaining multi-scale features, the feature map is restored via upsampling to maintain its dimensions. Extracting features from a reduced feature map can lead to information loss, particularly for smaller targets and intricate details. Skip connections are employed to integrate features after upsampling, enabling effective feature fusion. This approach preserves specific information, minimizes information loss, and enhances network expressiveness. Input and output data are combined through skip connections to retain information from the original scale. Finally, the GFR module performs splicing between its input and output, preserving spatial integrity while improving both accuracy and robustness.

2.2.3. Decoder

The decoder features an expansion architecture distinct from the encoder, facilitating gradual recovery of data details and spatial dimensions while maintaining precise feature extraction via interconnections. It comprises two phases: fusion and restoration. In the fusion phase, encoder outputs at all levels are processed by the dual-path dense attention (DPDA) module, enabling selective emphasis on pertinent features. The decoder begins by obtaining the encoder's output through a 3×3 convolution. The resulting feature maps are concatenated and then processed by the DPDA module following channel adjustment. To ensure that the attention mechanism preserves critical information, the pre-concatenated data is integrated into the attention output, maintaining the original feature distributions. During the restoration phase, a 3×3 deconvolution reconstructs the recovered features. Skip connections systematically combine the encoder's output

with the deconvolution, ensuring accurate feature recovery.

2.2.4. Dual-path dense attention module

The attention mechanism replicates human visual and cognitive processes, enabling the network to focus on critical information and thereby improving model performance and generalization.⁴⁶ Common attention mechanisms in CNNs include channel attention and spatial attention.^{47,48} The channel attention mechanism selectively emphasizes important channels by evaluating their significance and assigning higher weights.⁴⁹ The spatial attention mechanism follows a similar principle, enhancing adaptive learning of attention weights across regions to highlight significant areas.⁵⁰ In this work, the spatial attention mechanism is implemented via the DPDA module, as shown in Figure 1B. The DPDA module generates two multi-scale pathways via downsampling and applies identical attention operations to each pathway independently, preventing interference across scales and enabling more precise focus on key regions. Additionally, dense connections integrate outputs from all convolutions to produce a spatial attention feature map via 1×1 convolution. After applying a Sigmoid function, the feature map is multiplied by the pathway input, thereby integrating both paths to focus on critical information.

3. Construction of training set

The effectiveness of deep learning techniques is directly associated with the quality and generalizability of the training data. The validity of the HDEN model depends on both its intrinsic structure and the reliability of the dataset. The training dataset in this study comprises two components: a pure DAS signal dataset and a pure DAS noise dataset. Direct acquisition of pure DAS signals is impractical due to inevitable noise in real-world measurements. To address this, the pure DAS signal dataset is generated from noise-free forward modeling data, while the pure DAS noise dataset is obtained from field DAS recordings.

3.1. Pure distributed acoustic sensing signal set

Recently, some studies have employed seismic wavelets with different fundamental frequencies and propagation velocities to generate the synthetic records.² However, signals produced this way are overly simplistic and do not reflect field data characteristics. Consequently, models trained on such analog signals perform poorly at retrieving weak reflection signals.^{51,52} In contrast, we used a forward modeling method based on the wave equations to generate synthetic records, aiming to improve denoising accuracy. We used wave equations to simulate wavefield propagation and obtain synthetic records. Meanwhile,

the wave equation was activated by Ricker wavelets with fundamental frequencies ranging from 20 to 90 Hz. Furthermore, we used the finite difference method to solve the wave equation. Using the supplied stratigraphic profile data, we constructed a forward model that accurately represents the characteristics and structures of the strata. Finite difference equations are applied to solve the acoustic wave equation, effectively simulating seismic wave propagation through the geological layers. Based on prevailing conditions, 100 velocity models were generated by varying the thickness and density of the formations. Various wavelets with different center frequencies were used as inputs to the acoustic wave equation, producing 200 synthetic records. The detailed parameters for forward modeling are listed in Table 1. Parameters such as wavelet frequency and formation density were selected to span a wide range, enhancing data generalization and improving the model's denoising effectiveness. Figure 2 illustrates a representative forward model. Figure 2A shows a model with six distinct strata, each exhibiting an increasing wave velocity profile to simulate realistic stratigraphic conditions (1,500 m/s, 1,800 m/s, 2,200 m/s, 2,700 m/s, 3,300 m/s, and 4,000 m/s). The leftmost black vertical line indicates the DAS underground receiving line, while the red triangle 500 m away denotes the simulated source. The clean record in Figure 2B is generated by the forward model shown in Figure 2A. Using a sliding window technique, 18,159 clean DAS signal sets (64×64) were randomly extracted from the 200 synthetic records.

3.2. Pure distributed acoustic sensing noise set

Noise in DAS-VSP data arises from both environmental factors and inherent device interference, leading to a wide spectrum of DAS noise types. Interactions among these various noise types further increase the complexity of DAS-VSP noise. Consequently, noise generated solely through artificial simulation lacks precision and realism. To validate the pure DAS noise set, a diverse collection of typical noise segments—including fading, horizontal, and optical noise—was extracted from authentic DAS recordings without artificial stimulation sources. Combining multiple noise types enhances the neural network's ability to distinguish signals from noise. Here, we used noise data before the first arrival to construct the noise dataset, which contains only noise and no weak signals. Therefore, the denoising performance of the trained models can be further improved. On this basis, using a 64×64 sliding window, a total of 25,680 segments were extracted to create the pure DAS noise dataset.

3.3. Training process and training environment

During the training phase, we randomly selected one or more noise segments from the designated pure DAS noise set, then randomly extract a signal segment from the clean DAS signal set. To enhance training effectiveness, a random scaling factor between 0.3 and 3 is applied to the noise segments, which are then superimposed onto the signal segment, producing noisy records with varying SNRs. This process is iteratively repeated to generate 10,000 noisy records for network training, with the corresponding clean signal segments serving as network labels. The network is trained using mini-batch stochastic gradient descent to minimize the loss function, aiming to denoise DAS-VSP data so that the output closely matches the clean signals.

Experiments were conducted in MATLAB (2017b, MathWorks, USA) on a machine with an Intel(R) Core(TM) i5-9300H CPU at 2.40 GHz and an NVIDIA GeForce GTX 1050 GPU. The training batch size was set to 32, and training was performed over 60 epochs. The ADAM optimizer was used for network optimization. The learning rate was initially set to 10^{-4} and gradually decreased during training to 10^{-7} . Figure 3 shows the training and validation losses for HDEN. It is noted that all the losses are converged to small values, indicating the effectiveness of the training dataset and strategy.

4. Processing and analysis of the synthetic record

We employed HDEN to analyze synthetic recordings to assess its ability to distinguish signals from noise and examine the results. Synthetic records were generated similarly to the training set: clean DAS data were first generated by forward modeling and then combined with field noise. Figure 4A depicts the forward model used to generate the synthetic record, while Figure 4B shows the corresponding clean record after excitation. Figure 4C presents the noise record obtained from field data,

Table 1. Physical parameters of the forward model

Parameters	Specification
Wavelet	Ricker, single, and double
Central frequency (Hz)	20–90
Wave velocity (m/s)	1,000–5,000
Density (kg/m^3)	1,565–2,500
Interval (m)	1
Sampling frequency (Hz)	2,000

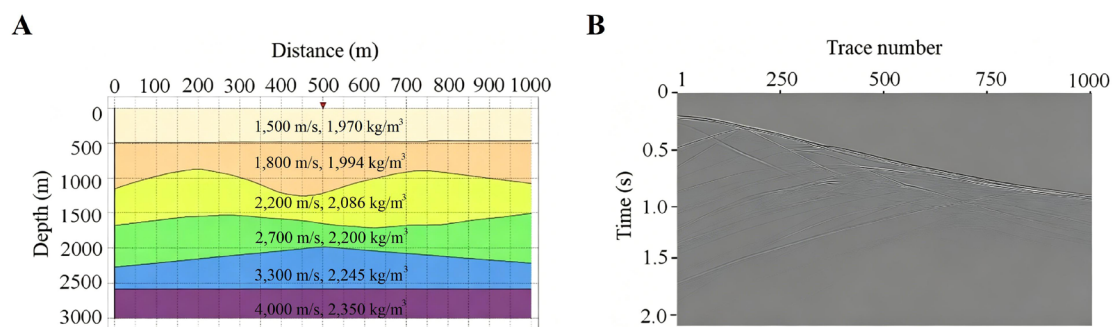


Figure 2. Construction of the pure synthetic record. (A) Stratigraphic model with velocity and density information; (B) The synthetic record.

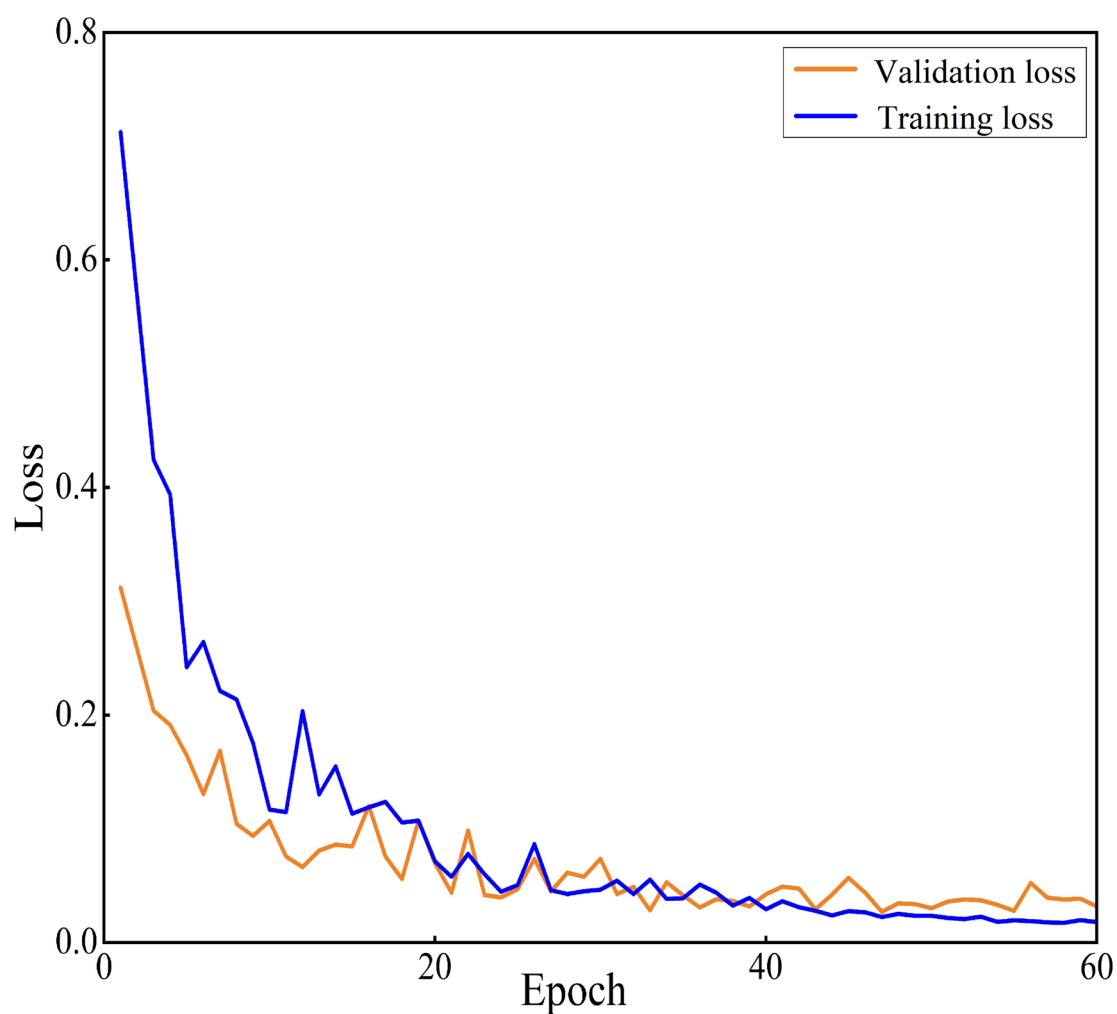


Figure 3. The training and validation losses for the hierarchical division encoder-decoder network

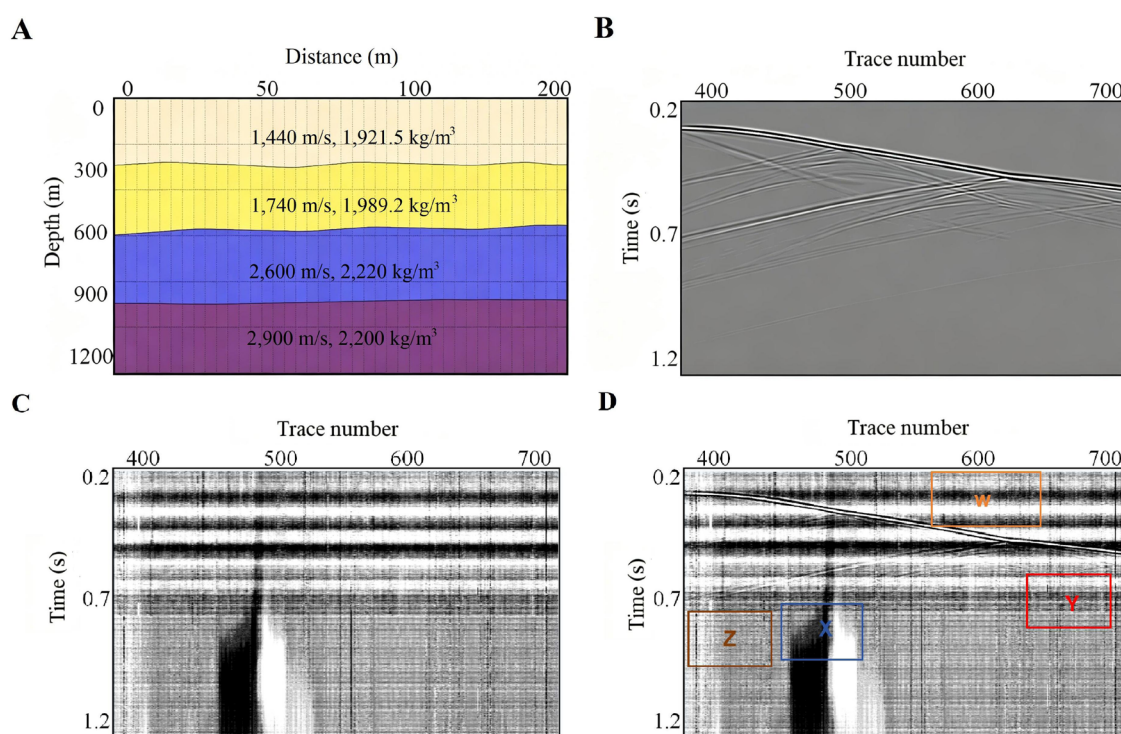


Figure 4. Noisy synthetic record. (A) Forward model. (B) Pure synthetic record. (C) Field noise record. (D) Noisy record (signal-to-noise ratio = -5 dB).

calibrated to match the actual noise distribution, including typical DAS-VSP noise types such as horizontal noise in box W, time-varying optical noise in box W, and fading noise in box Y. Figure 4D illustrates a synthetic test record produced by overlaying the clean and noisy records, resulting in an SNR of -5 dB. In this record, the overall signal is largely obscured by background noise, with only strong signals clearly visible, whereas the weak signal in box Z is difficult to discern due to substantial interference. We performed qualitative and quantitative evaluations of HDEN's denoising performance and compared the results with those obtained using singular value decomposition (SVD), WT, and DnCNN. To ensure the validity and fairness of the experiments, DnCNN and HDEN were trained under identical conditions.

4.1. Qualitative analysis

4.1.1. Analysis of denoising results

Figure 5 illustrates the denoising and local amplification results of SVD, WT, DnCNN, and HDEN. The SVD results in Figure 5B show poor noise reduction performance, with residual horizontal, fading, and time-varying optical noise. Signal recovery is effective only for high-energy signals. Amplification analysis in regions affected by time-varying optical noise reveals that multiple noise types hinder

the retrieval of weak signals. The WT results in Figure 5C exhibit the lowest denoising effectiveness, primarily addressing random noise while performing poorly against other noise categories; even prominent reflected signals are difficult to discern due to substantial residual noise. Figure 5D presents the outputs of DnCNN, showing a relatively clear background with significant noise suppression. However, DnCNN is inadequate in removing time-varying optical noise, as residual noise remains visible in the magnified image. Most signals can be reconstructed, preserving overall integrity, though some fine details are lost. Compared to traditional methods, deep learning improves both signal recovery and noise suppression, but the simple architecture of fully convolutional networks, such as DnCNN, limits feature extraction. In contrast, HDEN, also shown in Figure 5E, outperforms the other methods by effectively suppressing nearly all types of noise, including intense time-varying optical noise. Amplification results indicate that weak reflection signals can be fully and continuously restored, a feat not achieved using other techniques. These results confirm HDEN's superior denoising performance.

4.1.2. Analysis of amplitude retention characteristics

Figure 6 displays the filtered noise, evaluated to determine the effectiveness of each method in preserving signal

amplitude and validating DAS-VSP signal restoration. Figure 6A shows the original noise record, while Figures 6B–6E present the filtered results obtained using SVD, WT, DnCNN, and HDEN. Compared to the original noise, the SVD (Figure 6B) output revealed residual signals that became increasingly apparent when magnified in certain regions, indicating inadequate noise suppression. WT (Figure 6C) demonstrated limited denoising capability, effectively targeting random noise but failing to reduce other noise types, which complicated the identification of even prominent reflected signals. DnCNN (Figure 6D)

achieved significant noise reduction and preserved signal amplitude relatively well; however, residual signal leakage remained, highlighting its limitations in fully recovering weak signals. In contrast, HDEN (Figure 6E) employed a specialized encoder–decoder framework to effectively remove nearly all types of noise, including substantial time-varying optical noise. The filtered and amplified results show negligible residual signals, confirming that the original amplitude is largely preserved. Consequently, HDEN provided comprehensive restoration of formation data and outperformed the other methods in both amplitude preservation and denoising effectiveness.

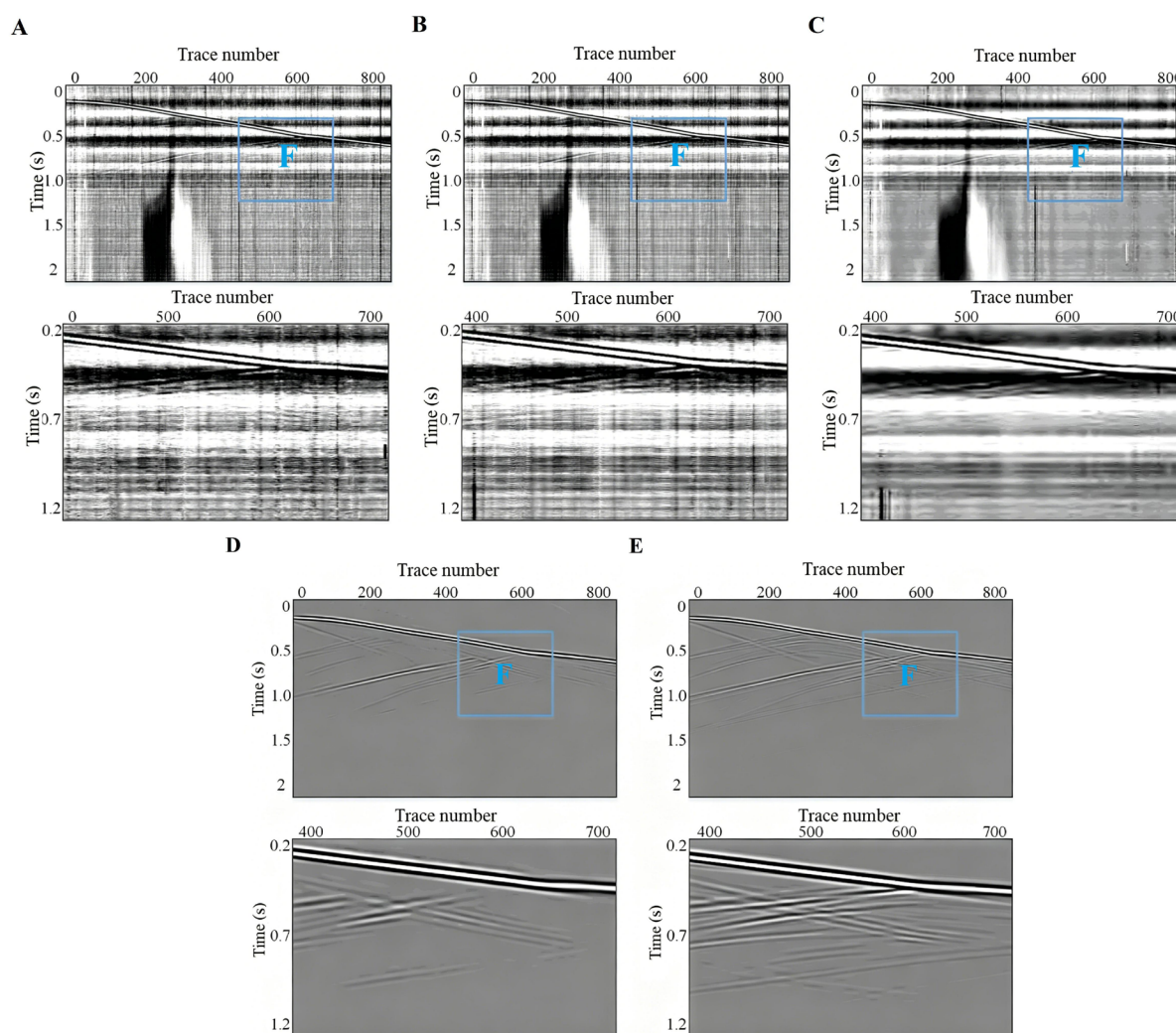


Figure 5. Denoising results of different methods. (A) Synthetic record and local magnification. (B)–(E) Denoising results (top subfigures) and local magnification (bottom subfigures) obtained using singular value decomposition, wavelet transform, convolutional denoising network, and hierarchical division encoder–decoder network. The boxed region magnifies the key detail to show the algorithm's noise suppression effect.

4.1.3. Frequency–wavenumber spectrum analysis

To comprehensively assess HDEN's denoising efficacy, we perform a comparison of compared frequency–wavenumber (F–K) spectrograms across several methods to elucidate frequency-domain behavior. Figure 7A shows the F–K spectrograms of the clean signal and noise. Figure 7B presents the denoised result and filtered noise after SVD processing. The SVD results are inadequate as residual noise remained, and both signal continuity and amplitude fidelity were compromised. Figure 7C displays the WT results, showing the least effective noise reduction and the greatest deviation from the pure recordings in the frequency domain. The denoising performance of DnCNN was slightly improved, as shown in Figure 7D. DnCNN efficiently removed most noise; however, residual frequency-domain components associated with noise persisted. Figure 7E presents the F–K spectrum of HDEN. Both the denoised output and the filtered noise closely resembled the F–K spectrum of the clean records. This comparison demonstrates that HDEN achieved superior denoising and better preserved signal integrity compared to other methods.

4.2. Quantitative analysis

4.2.1. Signal-to-noise ratio and root mean square error

A full and objective assessment of the denoising efficacy of various approaches necessitates more than a qualitative analysis alone. Consequently, we utilized two quantitative metrics: SNR² and root mean square error (RMSE).¹⁹ The definitions of SNR and RMSE are shown in Equations 4 and 5:

$$SNR = 10 \lg \left(\frac{\sum_{i=1}^x \sum_{j=1}^y S_{(i,j)}^2}{\sum_{i=1}^x \sum_{j=1}^y (N_{(i,j)} - S_{(i,j)})^2} \right) \quad (4)$$

$$RMSE = \sqrt{\frac{1}{xy} \sum_{i=1}^x \sum_{j=1}^y (N_{(i,j)} - S_{(i,j)})^2} \quad (5)$$

where the symbol S signifies the signal, whereas the other symbol N represents noise. Furthermore, the symbols i and j correspond to the dimensions of the data, and the symbols x and y correspond to the length and width of the signal, respectively. We applied these measures to the results from SVD, WT, DnCNN, and HDEN for different SNR levels. The resultant SNR and RMSE are displayed in Table 2. At 0 dB, SVD yields less than 1 dB of SNR improvement, while WT shows a significant improvement beyond 2 dB. Nonetheless, both methods are constrained by specific restrictions. The implementation of DnCNN improved SNR by around 13 dB, demonstrating the superior denoising efficacy of deep learning compared to conventional methods. Of the four approaches, HDEN demonstrated the greatest SNR enhancement, nearly 17 dB. The SNR of the processed findings declined progressively as the original record's SNR decreased. The performance of WT was markedly diminished under low-SNR conditions, whereas SVD and DnCNN maintained some noise-suppression efficacy. The previously indicated methods, however, do not sufficiently meet the criteria for the further processing of DAS-VSP data. The HDEN approach demonstrated considerable benefits in low SNR records, delivering an approximate 25 dB SNR enhancement even at –10 dB. HDEN's resilience enabled it to reliably produce superior denoising results across diverse SNR conditions.

4.2.2. Analysis on computational efficiency

In deep learning applications, the time required for training and testing is an important consideration. Table 3 presents the training and testing durations and the average SNR improvement for HDEN and the comparative approaches. SVD and WT reduced computational burden, as they

Table 2. Comparison of SNR and RMSE

Synthetic record/dB	SVD		WT		DnCNN		HDEN	
	SNR/dB	RMSE	SNR/dB	RMSE	SNR/dB	RMSE	SNR/dB	RMSE
0	0.9678	0.6471	2.1711	0.5634	12.8600	0.1646	16.8926	0.1053
–2	0.7192	0.6659	0.2038	0.7067	12.2583	0.1764	16.4430	0.1088
–4	0.4016	0.6907	–1.7683	0.8868	11.4172	0.1943	16.5735	0.1114
–6	–0.2013	0.7404	–3.7426	1.1131	10.2311	0.2228	15.4429	0.1262
–8	–0.9473	0.8068	–5.7249	1.3984	8.5656	0.2698	15.0434	0.1301
–10	–1.8501	0.8952	–7.7117	1.7578	6.3872	0.3468	14.6438	0.1340

Abbreviations: DnCNN: Convolutional denoising network; HDEN: Hierarchical division encoder–decoder network; RMSE: Root mean square error; SNR: Signal-to-noise ratio; SVD: Singular value decomposition; WT: Wavelet transform.

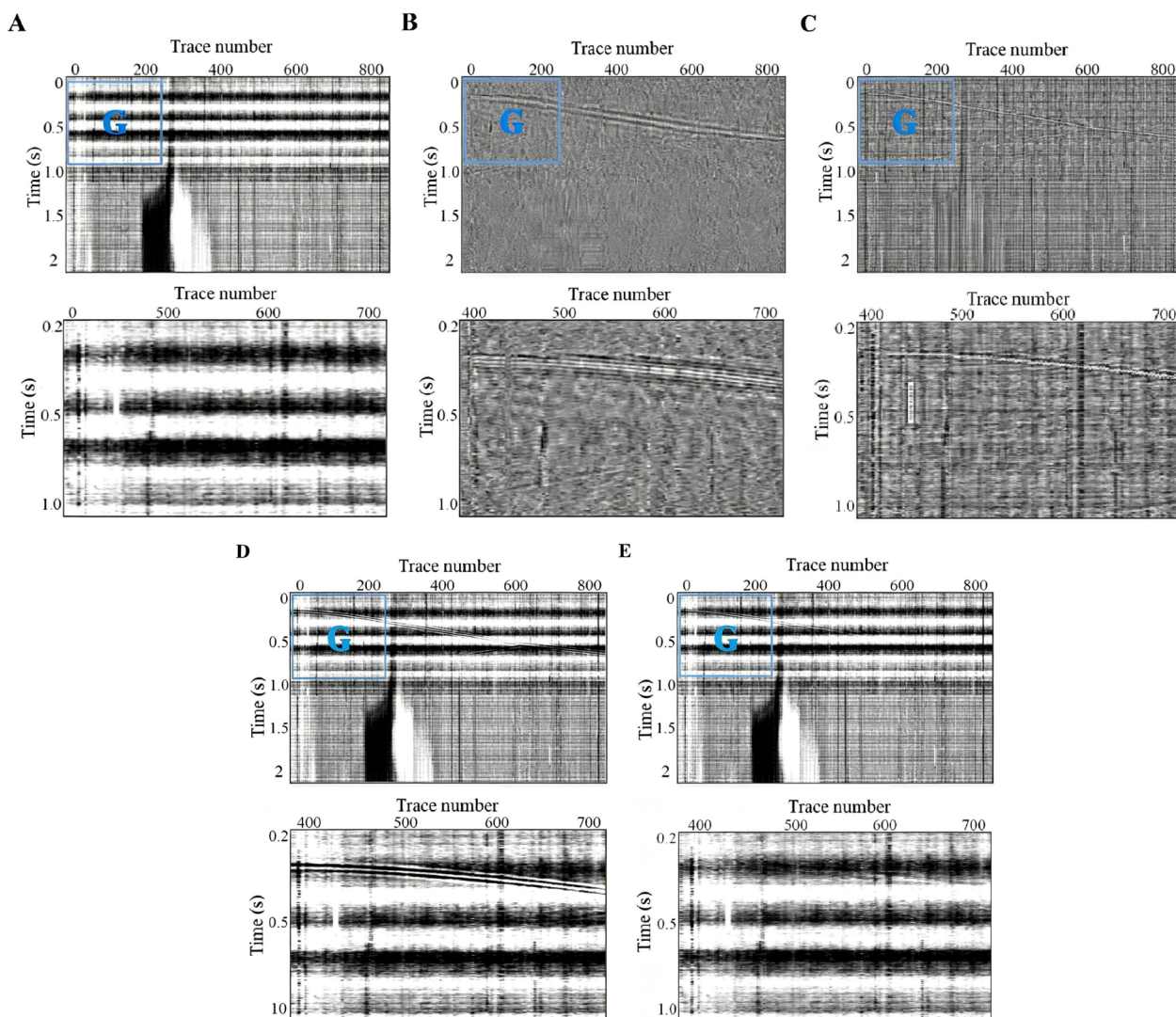


Figure 6. The filtered noise of different methods. (A) Pure noise record and local magnification. (B)–(E) The filtered noise (top subfigures) and local magnification (bottom subfigures) obtained using singular value decomposition, wavelet transform, convolutional denoising network, and hierarchical division encoder–decoder network. The boxed region magnifies another key detail, showing residual signals in the filtered result.

Table 3. The computational cost and improved SNR of different methods

Original record/dB	SVD	WT	DnCNN	HDEN
Processing time (s)	0.37	0.48	1.39	1.50
Training time (hour)	–	–	4.67	6.02
Averaged improved SNR (dB)	4.84	2.20	15.11	20.89

Abbreviations: DnCNN: Convolutional denoising network; HDEN: Hierarchical division encoder–decoder network; SNR: Signal-to-noise ratio; SVD: Singular value decomposition; WT: Wavelet transform.

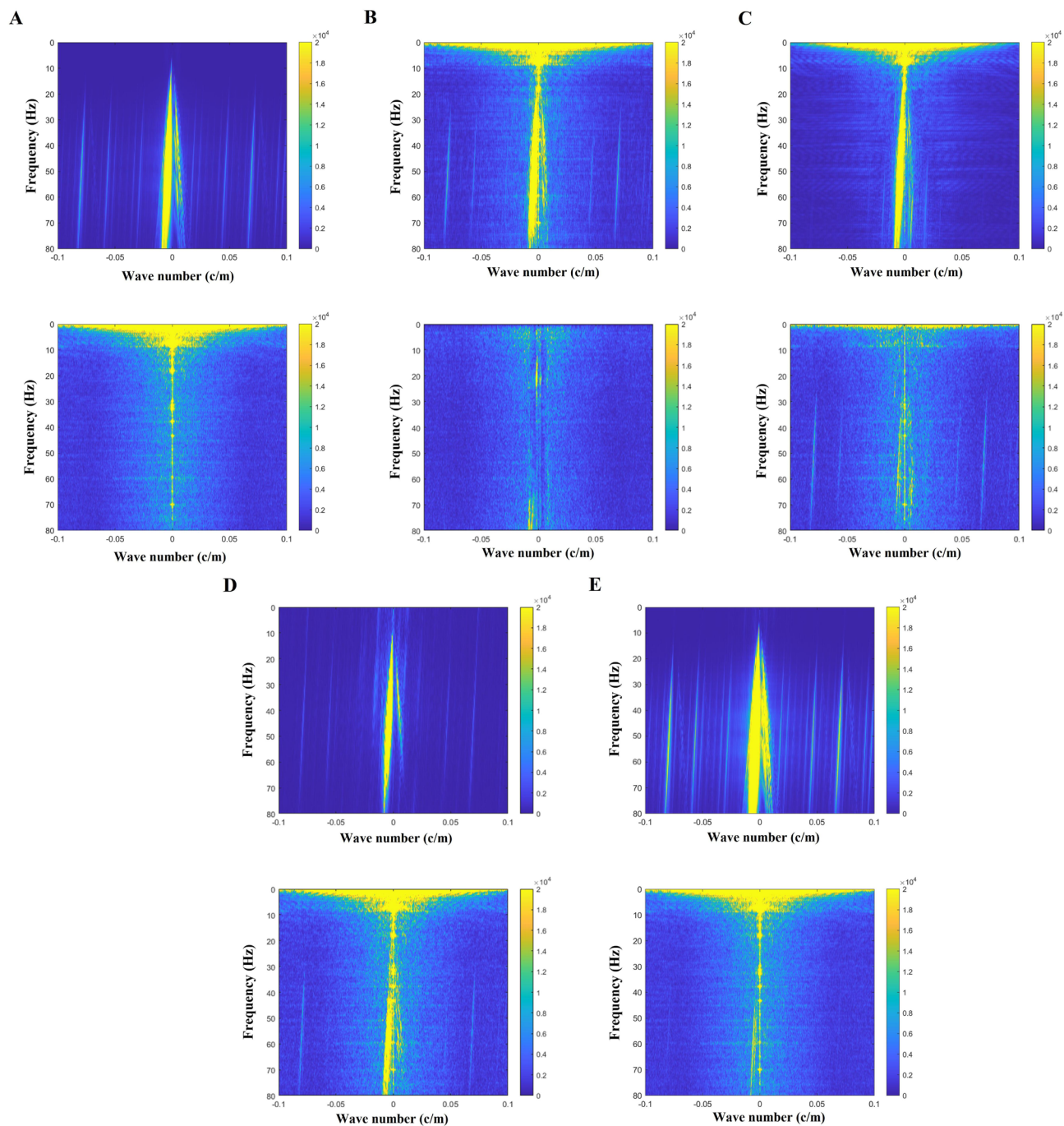


Figure 7. Frequency–wavenumber (F–K) spectra for different denoised results; (A) F–K results for pure signals and noise. (B)–(E) F–K results for recovered records (top subfigures) and removed noise (bottom subfigures) obtained using singular value decomposition, wavelet transform, convolutional denoising network, and hierarchical division encoder–decoder network.

did not require network training. While these methods enabled faster processing, their average SNR enhancement was insufficient to obtain high-quality DAS-VSP data. Both DnCNN and HDEN require considerable training time, with DnCNN being slightly faster. Nonetheless, deep learning techniques achieve substantially higher average SNR improvements than conventional methods, with HDEN achieving the largest enhancement, exceeding 20 dB on average. Given this significant gain in SNR and the rapid testing speed following a single training session, the time expenditure of deep learning approaches is justified. Consequently, HDEN offers significant advantages for efficiently and effectively processing DAS-VSP data.

5. Processing and analysis of the field records

Merely assessing denoising efficiency on synthetic data is inadequate for evaluating HDEN's efficacy in real-world scenarios. Consequently, we evaluated HDEN using DAS-VSP data collected in field conditions. Field recordings exhibit more complex signals and noise than synthetic data, necessitating a greater degree of signal-to-noise differentiation for efficient denoising. Acquiring clean signals in practical environments is difficult, rendering quantitative assessment impractical; hence, our comparisons are confined to qualitative evaluation.

5.1. Denoising results from field records

The field record utilized for testing is depicted in Figure 8A. The quality of the seismic data needs further improvement, as characterized by multiple noise types—such as random noise, time-varying optical noise, fading noise, and coupling noise—that obscure the signal and impede detection. Figure 8B illustrates the results from HDEN processing, demonstrating significant noise reduction. To enhance the demonstration of denoising efficacy, we magnified the

areas impacted by time-varying optical noise (box M) and coupling noise (box N). Figure 9 presents expanded views: Figure 9A illustrates the original records, Figure 9B depicts the denoised findings, and Figure 9C exhibits the filtered noise. The results demonstrate a significant improvement in recording quality, with improved continuity and clarity of previously distorted reflected signals. These data indicate that HDEN effectively manages low-energy transmissions and those with considerable noise interference.

5.2. Generalization analysis

To assess HDEN's denoising efficacy, we performed comparison analyses utilizing identical approaches on synthetic data. Figure 10A presents the outcomes of SVD. While some noise reduction is evident, the presence of residual noise and signal deterioration suggests that SVD is inadequate for successful denoising. Figure 10B illustrates the results for WT, which predominantly mitigates minor random noise but demonstrates limited overall efficacy. The deep learning methodology, illustrated by DnCNN, demonstrated significant efficacy in field-record processing, achieving high-quality recordings while minimizing noise, as shown in Figure 10C. Nonetheless, DnCNN is inadequate at recovering signals that are significantly affected by noise. Figure 10D demonstrates that HDEN surpasses these approaches, offering enhanced noise reduction and signal retention.

The area of box P is enlarged to improve visibility, as illustrated in Figure 11A–11D. SVD and WT were hindered by residual noise problems, complicating signal detection. While DnCNN mitigated noise to a certain degree, the extent of signal reconstruction in the denoised results and the signal leakage in the filtered results indicate that it failed to meet the requirement for subsequent data interpretation. The comparison of the magnified findings

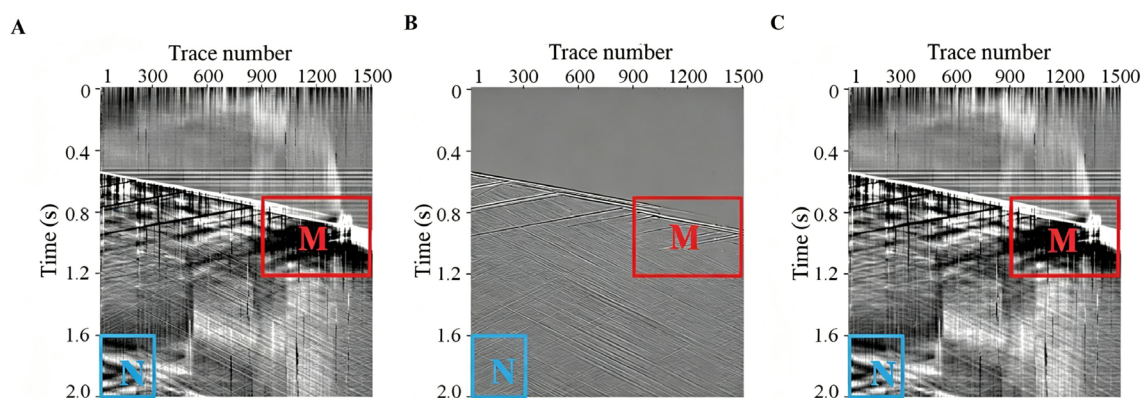


Figure 8. Processing result of the field record obtained using the hierarchical division encoder-decoder network. (A) Field record. (B) Denoising result. (C) Filtered noise. The red box highlights the severely noise-polluted region, while the blue box shows the weak signal area with mixed noise.

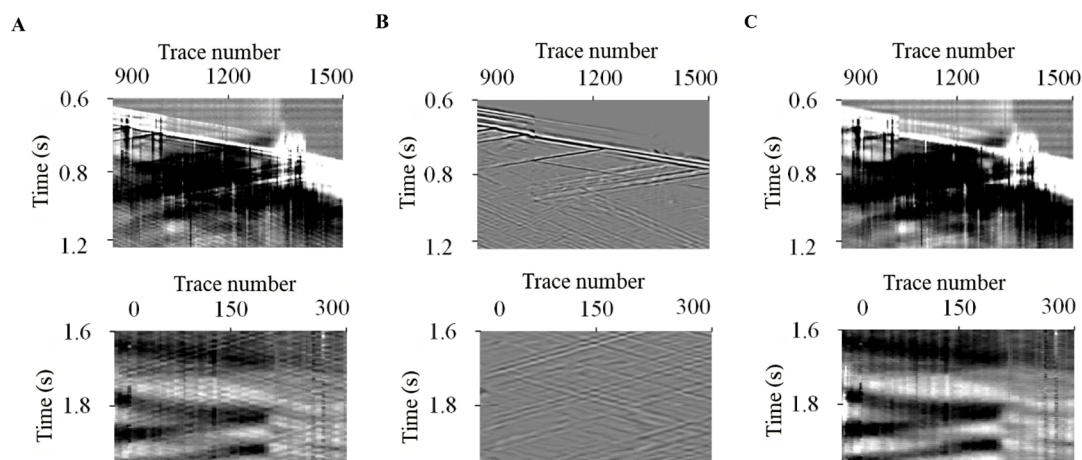


Figure 9. Local magnification result of the field record. (A) Magnified field noisy record of the area circled by boxes M and N shown in Figure 8. (B)–(C) Processing results and filtered noise (top: box M; bottom: box N) obtained using the hierarchical division encoder–decoder network.

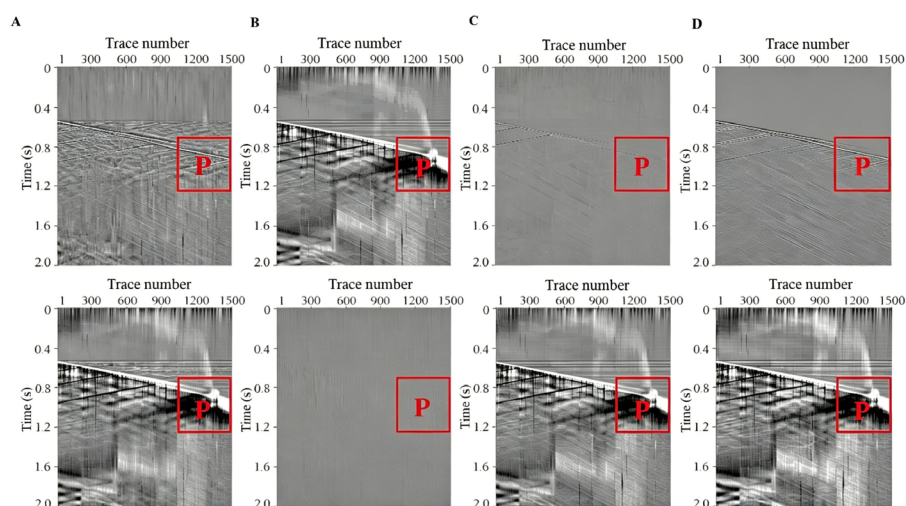


Figure 10. Comparison results for the processing of a field record. Denoising results (top subplots) and filtered noise (bottom subplots) for (A) singular value decomposition, (B) wavelet transform, (C) convolutional denoising network, and (D) hierarchical division encoder–decoder network, respectively.

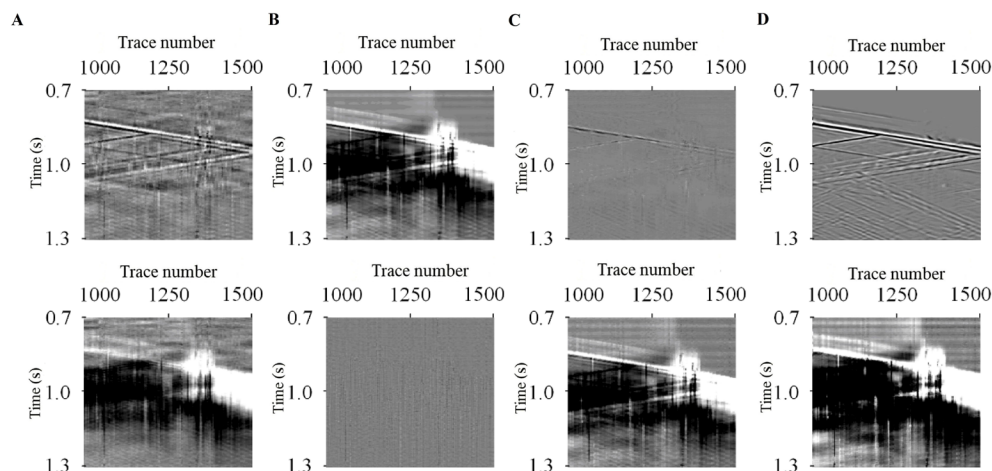


Figure 11. Comparisons of enlargements for different denoising methods. Denoising results (top subplots) and filtered noise (bottom subplots) for (A) singular value decomposition, (B) wavelet transform, (C) convolutional denoising network, and (D) hierarchical division encoder–decoder network, respectively.

further corroborates HDEN's outstanding denoising efficacy.

6. Conclusion

This study presents an HDEN for the effective separation of signal and noise in DAS-VSP data. HDEN first partitions information at a global scale and then processes it locally using the GFR module. This global-to-local approach ensures effective feature aggregation across all levels. The GFR module employs a multi-scale strategy to extract hierarchical features, enhancing feature representation. Furthermore, HDEN integrates a decoder with a spatial attention mechanism and skip connections, improving denoising performance and facilitating the integration of shallow and deep features.

The HDEN and several comparative methods were applied to both synthetic and field DAS data for performance evaluation. Qualitative analysis showed that HDEN effectively suppressed noise, recovered events masked by strong interference, and reduced signal leakage. Quantitative evaluation indicated that HDEN achieved the greatest SNR improvement across a range of SNR levels. These results demonstrate that HDEN enhanced the acquisition of high-quality DAS-VSP data, supporting more accurate seismic interpretation. In conclusion, HDEN exhibits substantial potential for broader applications in DAS-VSP data processing.

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Conflict of interest

The authors declare they have no competing interests.

Author contributions

Conceptualization: Li Han

Formal analysis: Li Han

Investigation: Dongyan Wang

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Visualization: Hang Yu

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Availability of data

Data are not openly available and are available upon reasonable request from the corresponding author.

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