

Dual-Direction Implicit Neural Representation for Seismic Scattered Noise Attenuation

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Abstract—Wide-azimuth (WAZ) land surveys often suffer from strong, nonstationary scattered noise generated by complex near-surface conditions. This interference is particularly prominent in far-offset prestack gathers and can severely degrade migration and azimuthal interpretation. Offset-vector-tile (OVT) sorting reorganizes WAZ data into azimuth- and offset-consistent single-fold volumes, providing a favorable domain for separating coherent reflections from scattered energy. However, existing OVT-domain noise attenuation techniques either rely on handcrafted transforms or supervised deep networks that require reliable clean labels, which are rarely available for field data. We propose *dual-direction implicit neural representation* (DINR) for scattered noise denoising, a fully unsupervised, data-adaptive framework that models each OVT gather as an implicit neural representation (INR). A lightweight coordinate-based multilayer perceptron (MLP) with Fourier-feature positional encoding is optimized directly on the target OVT data. To encourage the network to capture geologically plausible reflections while rejecting scattered components, we design a compound objective consisting of an ℓ_2 data fidelity term and a horizontal continuity regularization, coupled with early stopping for internal learning. Experiments on synthetic OVT volumes and field WAZ datasets demonstrate that DINR consistently suppresses scattered noise across offsets while preserving steeply dipping and weak reflections.

Index Terms—Implicit neural representation (INR), scattered noise attenuation, seismic data, unsupervised.

I. INTRODUCTION

SCATTERED noise is one of the most persistent challenges in land seismic processing. It is generated by strong near-surface heterogeneity, rugged topography, and complex weathering layers, producing diffracted and backscattered energy that is highly nonstationary in both space and time. In modern wide-azimuth (WAZ) surveys, scattered noise becomes especially severe at mid and far offsets, where it masks weak reflections, distorts amplitude-versus-offset/azimuth signatures, and degrades migration fidelity. Effective removal of scattered noise in prestack data is therefore essential for reliable imaging and subsequent reservoir characterization.

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Conventional prestack denoising methods typically rely on signal predictability or multiscale sparsity. Representative approaches include F-X prediction and Cadzow-type filtering [1], interpolation and prediction-based reconstruction for irregular sampling [2], multiscale directional transforms such as wavelets, curvelets, and seislets [3], and low-rank/SSA families [4]. These methods are often effective for stationary random noise, but scattered noise frequently overlaps reflections in scale and direction and varies rapidly across offsets, which limits the robustness of hand-tuned transform thresholds and prediction windows.

To better exploit WAZ redundancy and improve prestack coherence, offset-vector binning and offset-vector-tile (OVT) gathers reorganize CMP data into azimuth- and offset-consistent single-fold volumes [5]. Each OVT gather spans the full survey while preserving a narrow range of offset vectors, reducing acquisition footprint and enhancing spatial continuity [6]. Importantly, after CMP-to-OVT transformation, coherent reflections appear smoother within each tile, whereas scattered components become less organized across tiles, increasing separability. Transform-based OVT denoising methods such as 3-D continuous wavelet transform (3-D-CWT) leverage this 3-D coherence and remain strong practical baselines [7]. However, they still require careful parameter tuning and may attenuate steep dips or weak far-offset events when scattering is strong or spatially variable.

Deep learning has recently reshaped seismic denoising by learning data-driven priors from examples and suppressing complex noise more adaptively than handcrafted transforms. Supervised CNN and U-Net variants have been widely used for prestack random and erratic noise attenuation [8]. In the OVT context, supervised networks have shown promising efficiency and accuracy for strong scattered noise suppression in WAZ data [9]. Despite these successes, supervised models depend on clean labels or high-quality pseudolabels, which are difficult to obtain for field scattered noise. Their performance can also deteriorate when acquisition geometry or scattering statistics differ from the training distribution [10].

These limitations motivate label-free deep-learning strategies. Internal-learning and self-supervised frameworks optimize networks directly on the target noisy data, eliminating the need for external training sets. Deep image prior (DIP) and related seismic adaptations show that an untrained network can act as an implicit signal prior, recovering coherent events before fitting incoherent noise [11]. Recent developments include recursive DIP, early-stopped DIP, noise2noise style self-supervision, and physics-constrained variants [12], [13],

[14], [15], [16], [17]. However, CNN-based internal priors may still oversmooth fine prestack details or introduce texture-like artifacts due to fixed receptive fields.

Implicit neural representations (INRs) offer a powerful internal prior for seismic denoising by modeling data as continuous coordinate-to-amplitude functions parameterized with compact multilayer perceptrons (MLPs). Unlike convolutional priors that rely on fixed receptive fields, INRs represent the entire profile through a global, coordinate-conditioned function, which naturally favors coherent structures over incoherent fluctuations. When combined with positional encoding, INRs overcome the spectral bias of standard MLPs and can simultaneously fit smooth reflection continuity and preserve high-frequency waveform details in a data-adaptive manner [18]. Recent studies have demonstrated that this coordinate-based formulation is especially effective for seismic interpolation and reconstruction in challenging settings such as irregular land surveys and 5-D prestack volumes, where lateral consistency must be recovered from sparse or aliased observations [19]. Emerging INR denoising work further shows that fitting an implicit function directly to noisy seismic data can recover coherent events early in optimization while delaying the fit of incoherent noise, enabling label-free attenuation via internal learning [20].

In this letter, we propose *dual-direction INR* (DINR) for scattered noise denoising in OVT volumes. The training of DINR is partitioned into two successive phases: it first learns the spatial features within the inline direction and subsequently extends this learning to the crossline direction. By systematically processing both primary orientations, DINR transcends the limitations of traditional slice-by-slice methods and effectively honors the 3-D coherence of seismic wavefields. This leads to a significant refinement of reflections and a more robust suppression of nonstationary scattering. DINR augments a Fourier-feature INR with coordinate embeddings and a CNN decoder, enabling efficient, position-aware denoising while retaining the data-adaptive benefits of internal learning. DINR learns an INR of each OVT gather directly from the noisy data using Fourier-feature positional encoding. A structure-preserving objective combining robust data fidelity and horizontal continuity regularization, together with early stopping, guides the network to reconstruct coherent reflections while rejecting scattered interference. In Section II, we introduce the network architecture of INR and the loss function. In Section III, we use synthetic and field seismic data to prove the effectiveness of our method. Finally, we conclude in Section IV.

II. METHOD

A. Network Architecture of DINR

Leveraging the improved coherence of OVT gathers, we propose a label-free scattered noise attenuation framework based on INR, termed DINR. Inspired by NeRF [21], DINR treats each 2-D OVT profile as a sample of a continuous coordinate-to-amplitude function and learns this mapping directly from noisy data. Because reflections are coherent, they are fit early in optimization, whereas incoherent scattering is not.

The overall architecture is shown in Fig. 1. First, the normalized coordinate $\mathbf{v}$ of each profile is mapped via Fourier-feature mapping (FFM) to generate high-frequency positional features. These encoded coordinates are passed to an MLP, producing a latent embedding $\boldsymbol{\varphi}$. Finally, a lightweight CNN decoder reconstructs the denoised profile from $\boldsymbol{\varphi}$. This hybrid INR–CNN structure combines continuous implicit modeling with spatial feature extraction, enabling DINR to preserve lateral continuity while suppressing scattered noise.

The training procedure for DINR is conducted in two successive stages. In Stage 1, the model is optimized by mapping profile indices along the inline dimension to establish an initial structural foundation. Subsequently, in Stage 2, the denoised profiles from the first stage are utilized as the input basis for a second independent training phase focused on the crossline dimension. By sequentially incorporating information from both dimensions, the framework effectively reconciles structural features to yield the final 3-D denoising result.

B. Input Representation

Prestack WAZ data are first organized into CMP gathers and then transformed to OVT volumes.

- 1) *Profile Extraction and Clipping*: Each OVT tile is reorganized into a sequence of 2-D profiles along one spatial axis. Within each profile, amplitudes exceeding the 99.98th percentile (absolute values) are clipped to mitigate heavy-tailed scattering effects caused by the thick loess layer. This prevents anomalous energy from dominating the optimization, while the inherent continuity of the INR framework ensures that any affected valid signals are effectively reconstructed through spatial coherence.
- 2) *Coordinate Normalization*: The profile index is linearly mapped to $[0, 1]$ based on the sample count as the network's input coordinate. This definition remains strictly consistent across the dual-direction training stages to ensure a uniform numerical range for stable optimization. After preprocessing, each OVT profile is treated as a coordinate-indexed amplitude field with a normalized coordinate v_i and amplitude $\mathbf{F}(v_i)$.

C. Implicit Representation Formulation

DINR models each OVT profile using a compact INR. Given profile index v_i , Fourier positional encoding produces

$$\gamma(v_i) = [\sin(2\pi b^0 v_i), \cos(2\pi b^0 v_i), \sin(2\pi b^{L-1} v_i), \dots, \cos(2\pi b^{L-1} v_i)] \quad (1)$$

where b is the base frequency and L is the encoding dimension [18]. The encoded coordinates are mapped to a latent embedding

$$\boldsymbol{\varphi} = \text{MLP}(\gamma(v_i)) \quad (2)$$

and the denoised output is obtained by the decoder

$$\hat{\mathbf{F}} = f_{\Theta}(\boldsymbol{\varphi}) = f_{\Theta}(\text{MLP}(\gamma(v_i))). \quad (3)$$

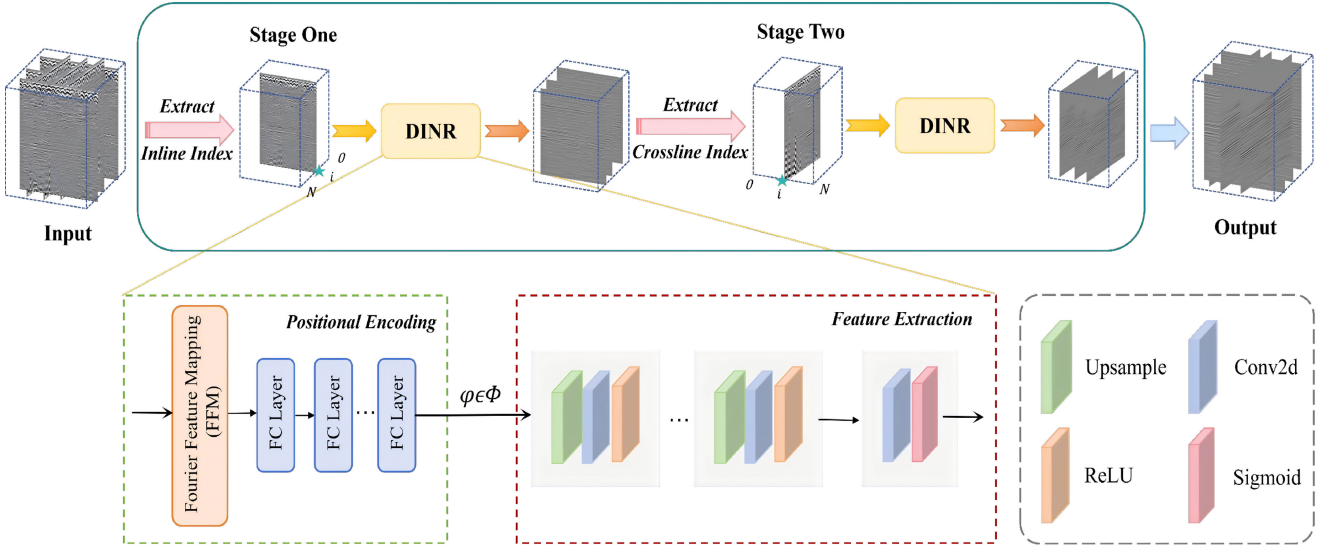


Fig. 1. Overall DINR architecture. For each OVT profile, coordinates are Fourier-encoded and mapped to a latent embedding φ by an MLP; a CNN decoder reconstructs the denoised profile from φ .

This encoding expands the effective bandwidth of the MLP so it can represent smooth reflection continuity and high-frequency details simultaneously.

The DINR hybrid architecture partitions denoising into global structural modeling and local refinement. The coordinate-based MLP serves as the structural foundation; by leveraging its inherent continuity bias, it acts as a global estimator to capture long-range coherence and reconstruct the primary seismic "skeleton." Subsequently, the CNN decoder applies spatial constraints to enhance lateral continuity and resolve high-frequency details, effectively compensating for the MLP's spectral bias. This cascaded design ensures robust noise suppression while preserving signal integrity and preventing leakage.

D. Loss Function and Optimization

DINR is trained to reconstruct coherent reflections while avoiding overfitting scattered noise. Let $\mathbf{F}$ denote the noisy input profile and $\hat{\mathbf{F}}$ the INR output.

We implement the reconstruction term with mean squared error (mse) to preserve amplitudes

$$L_{recon} = \frac{1}{N \cdot H \cdot W} \sum_{n=1}^N \|\hat{\mathbf{F}}^n - \mathbf{F}^n\|_F^2 \quad (4)$$

where $\mathbf{F}$ represents the input noisy OVT slice; $\hat{\mathbf{F}}$ represents the reconstructed output; n represents the n th profile; N represents the number of seismic profiles; and H and W represent the number of samples in the time and spatial dimensions, respectively.

Because scattered noise is spatially irregular whereas reflections are laterally coherent, we impose a horizontal continuity constraint on the output

$$L_{horizontal} = \frac{1}{N \cdot H \cdot W} \sum_{n=1}^N \sum_{i,j} |\hat{\mathbf{F}}_{i+1,j}^n - \mathbf{F}_{i,j}^n|. \quad (5)$$

The final objective loss is

$$L_{total} = L_{recon} + \lambda L_{horizontal} \quad (6)$$

where L_{recon} enforces fidelity and $L_{horizontal}$ penalizes incoherent lateral variability. The hyperparameter λ serves as a regularization weight to balance data fidelity against the spatial smoothness constraint, effectively suppressing nonstationary scattered noise while preserving the lateral continuity of seismic events.

III. EXPERIMENTS

In the DINR experiments, we implement a sequential training strategy to capture multidimensional coherence. In particular, the network is first trained using frame indices along the inline direction as input. Upon obtaining the unidirectional results, the model is further trained using frame indices from the crossline direction. This cascading approach yields the final dual-directional representation for scattered noise attenuation. To verify the effectiveness of DINR for scattered noise suppression, we conduct experiments on both synthetic OVT data and field WAZ OVT datasets. The 3-D-CWT [7] is used as a representative conventional baseline. Beyond comparing denoised OVT profiles, we further inspect CMP gathers extracted from the denoised OVT volumes and stacked denoising results to evaluate fidelity and practical imaging impact.

The DINR framework is implemented in PyTorch 1.12.0 and optimized using the Adam algorithm (batch size 16) on an NVIDIA RTX 3090 GPU. The architecture comprises a 512-D MLP hidden layer followed by a CNN decoder with five NeRV blocks (strides: [5, 2, 2, 2, 2]). Each block integrates bilinear upsampling, 3×3 convolutions, batch normalization, and ReLU, with a final 1×1 convolution for seismic reconstruction. For positional encoding, Fourier mapping dimensions L are set to 20 for synthetic data and 80 for field data ($b = 1.25$). Training utilizes a fixed learning rate

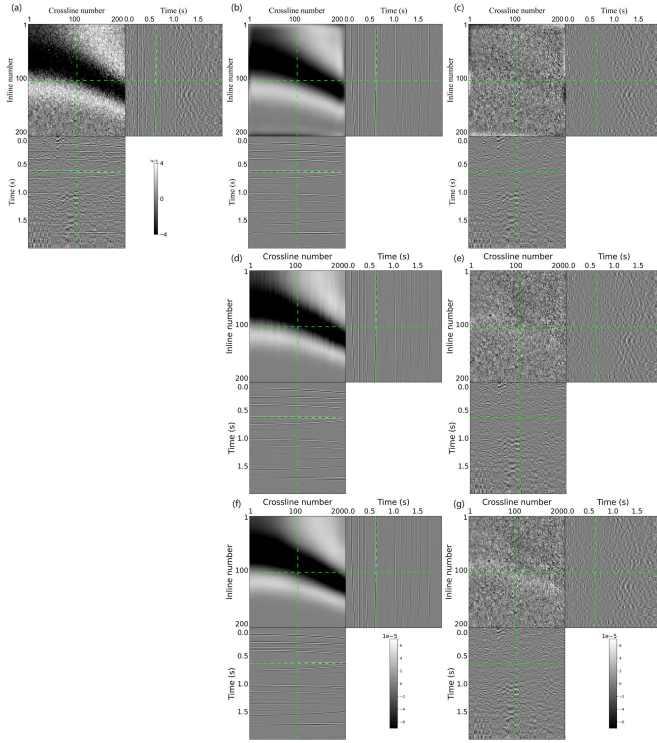


Fig. 2. Comparative results on the synthetic OVT dataset. (a) Noisy input. (b) 3-D-CWT denoising result. (c) Residual noise removed by 3-D-CWT. (d) Unidirectional DINR denoising result. (e) Residual noise removed by unidirectional DINR. (f) Dual-directional DINR denoising result. (g) Residual noise removed by dual-directional DINR.

of 5×10^{-4} , a regularization weight $\lambda = 0.2$, and an early stopping strategy at 35 and 70 epochs for synthetic and field datasets.

A. Synthetic Data Experiment

Synthetic Dataset: We construct a clean synthetic midoffset OVT profile containing coherent reflection events with varying curvatures and time intercepts. To emulate realistic scattering conditions, we contaminate this clean reference with field-derived scattered noise. The resulting signal-to-noise ratio (SNR) is -5.7 dB. The noise component was extracted from field midoffset OVT data by suppressing coherent reflections via 3-D-CWT. This noise is highly nonstationary and shares a similar spectral bandwidth with the reflections, creating a challenging benchmark representative of complex WAZ OVT environments.

Fig. 2 shows the comparison of 3-D-CWT, unidirectional DINR, and dual-directional DINR on synthetic OVT profiles. While 3-D-CWT improves the SNR to 11.0 dB, its fixed local windows introduce boundary errors and struggle with spectral overlap. Conversely, DINR leverages global INR feature learning to adaptively disentangle reflections from nonstationary scattering across the full aperture, enhancing waveform sharpness and lateral continuity. Crucially, the dual-directional approach eliminates the “vertical stripe” artifacts inherent to the unidirectional variant, boosting the SNR to 15.76 dB. Although this bidirectional strategy doubles the

TABLE I
SNR COMPARISON OF THE ABLATION EXPERIMENTS
ON SYNTHETIC DATA

Method	SNR (dB)	Improvement (dB)
Noisy Data	-5.7	-
MLP-only	7.51	+13.21
CNN-only	11.66	+17.36
Unidirectional DINR	15.22	+20.92

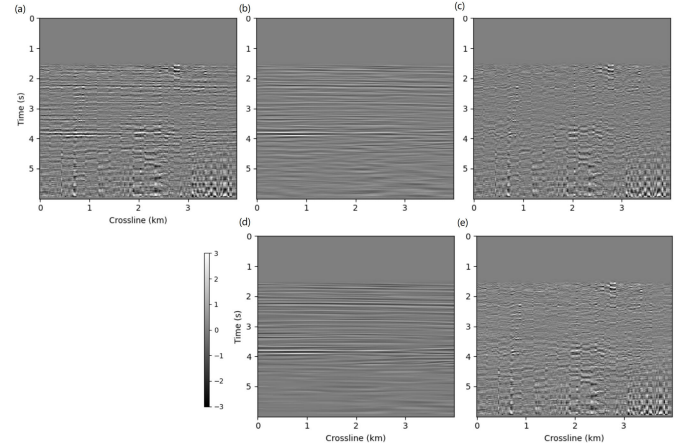


Fig. 3. Midoffset inline OVT profiles. (a) Original profile. (b) Denoised result using 3-D-CWT. (c) Scattered energy removed by 3-D-CWT. (d) Denoised result using DINR. (e) Scattered energy removed by DINR.

training time (3 versus 1.5 min), it substantially enhances denoising fidelity and structural consistency.

Ablation: To investigate the contribution of each component within the hybrid DINR architecture, ablation experiments were conducted on the synthetic dataset (Table I). Utilizing only the MLP relies on its inherent continuity bias to reconstruct the global structure, improving the SNR from -5.7 to 7.51 dB. The standalone CNN reaches an SNR of 11.66 dB, highlighting its superior feature extraction for noise suppression. Ultimately, the unidirectional DINR achieves the highest SNR of 15.22 dB by synergizing the MLP’s structural foundation with the CNN’s spatial consistency. This validates that the hybrid INR–CNN design is essential for robust noise attenuation while preserving effective signals.

B. Field Data Experiment

We employ a 3-D WAZ land survey acquired in the Gobi Desert of western China, characterized by strong near-surface heterogeneity and rugged topography that generates intense scattered noise. To capture this offset-dependent behavior and assess robustness under varying noise conditions, we evaluate DINR separately on near-offset and midoffset OVT datasets.

Fig. 3 displays a representative midoffset inline profile. While 3-D-CWT removes most scattering in Fig. 3(b), its fixed windowing tends to oversmooth the profiles under high-amplitude noise, attenuating weak reflectors and reducing lateral continuity. Conversely, DINR yields a cleaner, more continuous reconstruction in Fig. 3(d) without introducing artifacts. By exploiting the enhanced within-tile coherence

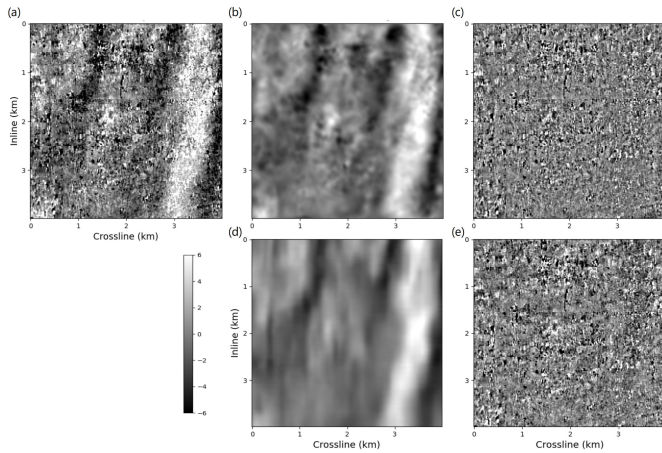


Fig. 4. Near-offset OVT time slice comparison at 2 s. (a) Original time slice. (b) 3-D-CWT denoising result. (c) Scattered energy removed by 3-D-CWT. (d) DINR denoising result. (e) Scattered energy removed by DINR.

of OVT sorting, DINR's implicit structural prior effectively suppresses incoherent scattering while preserving subtle reflections.

Fig. 4 shows the comparison of representative near-offset time slices at 2 s. Across all offsets, 3-D-CWT suppresses most scattered energy and leaves only weak residual noise. DINR further attenuates the remaining incoherent scattering while better preserving spatial integrity. This is notably apparent in the challenging near-offset profiles. DINR achieves stronger scattering attenuation, confirming that adaptive INR fitting in the OVT domain robustly handles WAZ scattering variations.

Regarding computational efficiency, the bidirectional training on field data takes approximately 25 min, compared to 13 min for the unidirectional version. This increased cost is a justifiable tradeoff for the substantial gains in structural continuity and nonstationary noise suppression.

IV. CONCLUSION

We presented DINR, a deep internal-learning framework for scattered noise removal in WAZ prestack data in the OVT domain. By converting CMP gathers into azimuth- and offset-consistent OVT volumes, reflections become more laterally coherent while scattered energy is less organized, enabling more effective separation. DINR models each OVT profile with an INR and optimizes it directly on the noisy data using Fourier-feature positional encoding. A compound loss combining reconstruction fidelity and horizontal continuity regularization, together with early stopping, guides the network to recover coherent reflectors while suppressing incoherent scattering.

Synthetic experiments show that DINR improves SNR from -5.7 to 15.76 dB, outperforming 3-D-CWT. Field WAZ examples further demonstrate robust suppression of strong near-offset scattering and improved reflector continuity in both OVT and extracted CMP gathers, with cleaner stacked sections. These results indicate that DINR provides a practical,

label-free alternative for prestack scattered noise attenuation in modern OVT processing workflows.

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